MVP-Human Dataset for 3D Human Avatar Reconstruction from Unconstrained Frames

Xiangyu Zhu, Tingting Liao, Jiangjing Lyu, Xiang Yan, Yunfeng Wang, Kan Guo, Qiong Cao, Stan Z. Li, and Zhen Lei

1National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences
2Alibaba Group
3Speechocean
4Westlake University

{xiangyu.zhu,tingting.liao,zlei}@nlpr.ia.ac.cn, {jiangjing.lijj,weishan.wyf,guokan.gk}@alibaba-inc.com, caoqiong@speechocean.com, Stan.ZQ.Li@westlake.edu.cn

ABSTRACT

In this paper, we consider a novel problem of reconstructing a 3D human avatar from multiple unconstrained frames, independent of assumptions on camera calibration, capture space, and constrained actions. The problem should be addressed by a framework that takes multiple unconstrained images as inputs, and generates a shape-with-skinning avatar in the canonical space, finished in one feed-forward pass. To this end, we present 3D Avatar Reconstruction in the wild (ARwild), which first reconstructs the implicit skinning fields in a multi-level manner, by which the image features from multiple images are aligned and integrated to estimate a pixel-aligned implicit function that represents the clothed shape. To enable the training and testing of the new framework, we contribute a large-scale dataset, MVP-Human (Multi-View and multi-Pose 3D Human), which contains 400 subjects, each of which has 15 scans in different poses and 8-view images for each pose, providing 6,000 3D scans and 48,000 images in total. Overall, benefits from the specific network architecture and the diverse data, the trained model enables 3D avatar reconstruction from unconstrained frames and achieves state-of-the-art performance. We release the multi-pose scans, multi-view images and labelled 3D skeletons in MVP-Human at http://www.to-be-released.com.

CCS CONCEPTS

• Computing methodologies → Shape inference.

KEYWORDS

3D avatar reconstruction, 3D human data, 3D body reconstruction, dataset

1 INTRODUCTION

Image based 3D human reconstruction has been widely applied in many fields such as VR/AR experience (E.g., movies, sports, games), video editing and virtual dressing [5, 33]. To reconstruct 3D human, current methods always hold some strong assumptions on the input.
3D stereo [24, 34, 39] relies on camera calibration and a fully constrained environment. Human performance capture [14, 15], which tracks human motion and deforms 3D surface using weak multi-view supervision, needs a person-specific template before reconstruction. 3D reconstruction from single-view video fuses dynamic human appearances into a canonical 3D model, which is related to our tasks. However, the subject is asked to hold a rough A-pose during images collection, which is not fully unconstrained. Besides, they either fit the SMPL model [1, 2] or coarsely morph the naked body according to the silhouette [3], which loses the fine-grained detail. Recently, single-image based reconstruction [16, 18, 30, 31] learns the implicit 3D surface based on aligned image features, recovering remarkable clothes details. However, as an ill-posed problem, single-image reconstruction suffers from unsatisfactory artifacts on the back. When these methods are extended to a multi-view setting, the camera calibration are still needed [30, 31].

To make 3D avatar reconstruction more accessible, we explore a novel problem that reconstructs a 3D avatar from unconstrained frames, where no requirement on cameras or actors is needed. This task is extremely challenging due to the requirement of fusing multiple snapshots in diverse views and poses into a single reconstruction. Besides, when reconstructing the geometry details, the local feature in each frame may not be reliable due to the inevitable misalignment in unconstrained environments, leading to overly smooth reconstruction results. Moreover, the model training relies on special training data that each person should have multi-view-and-pose images and the corresponding 3D shape in T-pose, which is inaccessible to the public.

To address these challenges, we first create a new Multi-View multi-Pose 3D Human dataset (MVP-Human) with 400 subjects, each having 15 scans in different poses and 8-view images for each pose, proving 6,000 3D scans and 48,000 images in total. The linear blend skinning weights are also provided not only for supervising the model training, but also for reposing the captured T-pose meshes to the strict canonical pose, which is regarded as the target of 3D reconstruction models. Besides, benefit from the collected multi-view images, we enable quantitative evaluation on real-world inputs, which is more reliable than the commonly used rendered meshes [18, 30, 31].

Based on MVP-Human, we introduce 3D Avatar Reconstruction in the wild (ARwild), a deep learning based method aiming to reconstruct a 3D avatar, including the T-pose shape and skinning weights, from multiple frames in unconstrained poses and views. Specifically, we propose a SKinning weights Network (SKNet) to predict the Linear Blend Skinning (LBS) [21] in T-pose, by which each 3D point finds the corresponding pixel in each frame. Then the aligned image features are adaptively fused by a Surface Reconstruction Network (SRNet) to predict the final 3D shape as an implicit function [30]. A brief-view of the framework is in Fig. 1.

In summary, the main contributions of the work are:

1. We create a large 3D human dataset where high-resolution 3D scans and real images are collected in a multi-pose and multi-view setting. Sophisticated labeling including 3D skeleton landmarks and linear blend skinning weights are also provided. All the data is promised to be released when the paper is accepted.

2. We propose ARwild to reconstruct a clothed 3D avatar from unconstrained frames, independent of any camera calibration, person-specific template or constrained actions. This method extends the deployment of passive 3D human reconstruction and benefits many AR/VR applications.

3. Our method achieves high-quality 3D reconstruction results in the new task where only unconstrained frames are provided. Besides, our method produces reconstructions of higher accuracy compared to the state-of-the-art methods, validated qualitatively and quantitatively in the experiments.

2 RELATED WORKS

3D human reconstruction methods can be roughly classified by the assumptions hold on the input, including special equipment, person-specific template, and constrained actions. In this section, only the methods that take RGB inputs are discussed.

Multi-view Stereo Reconstruction: Multi-view acquisition approaches capture the scene from multiple synchronized cameras, and build the 3D shape from photometric cues. Stereo based methods [12, 34, 37, 39] achieve remarkable performance by optimizing multi-view stereo constraints from a large number of cameras. The geometric detail can be further improved by active illumination [37, 40]. Benefit from deep learning, recent works [8, 13, 17, 19, 20] reduce the camera number to very sparse views. Compared with these methods, we only need one camera without calibration.

Human Performance Capture: Most of the methods assume a pre-scanned human template and reconstruct dynamic human shapes by deforming the template to fit the images. Prior methods [9, 10, 34] require a number of multi-view images as inputs, and align the template to observations using non-rigid registration. MonoPerfCap [41] and LiveCap [14] enable posed body deformation from a single-view video by optimizing the deformation to fit the silhouettes. Recently, DeepCap [15] employs deep learning to estimate the skeletal pose and non-rigid surface deformation in a weakly supervised manner, constrained by the multi-view keypoint and silhouette losses. DeepMultiCap [47] further extends DeepCap to the multi-person scenario. Our method shares the same input formulation, single-view RGB video, with some of these methods, but we do not need a pre-scanned template.

3D Avatar Reconstruction: Early works [29, 42, 45] employ statistical body models such as SCAPE [4] or SMPL [25] to recover human models which is typically animatable. However, parametric models cover limited shape variations due to the restriction of PCA shape space. Recently, some methods try to recover a clothed 3D avatar from a monocular video in which a person is moving. Alldieck et al. [3] ask the target subject to turn around in front of the camera while roughly holding the A-pose. Then the dynamic human silhouettes are transformed into a canonical frame of reference, where the visual hull is estimated to deform the SMPL model. This method is further improved by [2] on fine-level details reconstruction by introducing more constraints like shape from shading. Octopus [1] encodes the images of the person into pose-invariant latent codes by deep learning, and fuses the information to a canonical T-pose shape, achieving faster prediction. Such methods share
the same goal of reconstructing canonical-pose shape from monocular video with our method, but we do not require the subject to perform specific actions.

Recently, neural-network-based implicit function [7] is introduced to represent 3D human, demonstrating significant improvement in representation power and fine-grained details than voxel [35] and parametric models [25]. PIFu [30] aligns individual local features at the pixel level to regress the implicit field (inside/outside probability of a 3D coordinate), enabling the 3D reconstruction from a single image. PIFuHD [31] extends PIFu to a coarse-to-fine framework so that a higher resolution input can be leveraged for achieving high fidelity. MonoPort [23] proposes a faster rendering method to accelerate inference time. ARCH [16, 18] reconstructs a human avatar in the canonical pose from a single image, where the image features are aligned by a semantic deformation field. These methods hold the minimum assumptions, one unconstrained image, on the input, and show state-of-the-art performance, but they suffer from depth ambiguity and unsatisfactory artifacts on the back. It is worth noting that PIFu can be extended to multiple views [30, 31], but camera calibration is still needed in the scenario.

3D Human Data: Several works have released their 3D clothed human data, summarized in Tab. 1. Multi-Garment [5] and THuman 2.0 [43] release a large number of scans with various body shapes and natural poses, which have been well employed in single-view and multiview reconstructions [48]. However, the single scan for each subject is not suitable for our task that depends on multi-pose scans. BUFF [44] and CAPE [7] capture 4D people performing a variety of pose sequences, which are compatible with our task but the subject number is rather limited. THuman [48] consists of 200 people in rich poses, but the captured 3D meshes lose fine-grained geometry with only 10k points. Compared with existing datasets, MVP-Human demonstrates particularity by its multi-pose scans of hundreds of people, high-quality scans (10k vertices) and unique multiview real (not rendering) images.

| Dataset          | Year | # of subjects | # of scans | vertices per. scan | multi-pose scans per | multi-view images per |
|------------------|------|---------------|------------|-------------------|----------------------|----------------------|
| BUFF [44]        | 2017 | 5             | 11,054     | 150k              | ✓                    | -                    |
| Multi-Garment [5]| 2019 | 96            | 356        | 55k               | -                    | -                    |
| THuman [48]      | 2019 | 230           | 7,000      | 10k               | ✓                    | -                    |
| CAPE [?]         | 2020 | 11            | 80,000     | 7k                | ✓                    | -                    |
| THuman 2.0 [43]  | 2021 | 500           | 500        | 289k              | -                    | -                    |
| MVP-Human        | 2022 | 400           | 6,000      | 100k              | ✓                    | ✓                    |

Table 1: Comparison of MVP-Human to other public clothed 3D human datasets. The column “multi-pose scan per.” denotes that there are multi-pose scans for each subject. The column “multi-view images per.” denotes that there are camera-captured multi-view images for each scan.

3.1 Pixel Alignment via Skinning Weights
PIFu [30] has demonstrated that the pixel-aligned image feature is the key to reconstructing detailed 3D surfaces. However, different from single-image reconstruction [30, 31], where posed human is naturally aligned with the image space, the retrieval of 2D projected coordinates \( x_1, x_2, \ldots, x_V \) for the 3D point \( X \) is not straightforward due to the unknown views and poses of the input frames.

To rebuild the canonical-to-image correspondence, we employ a skeleton-driven deformation method. Specifically, each 3D vertex on the body surface can be transformed to any poses using a weighted influence of its neighboring bones, defined as \( w = \{ w_k \}_{k=1}^K \) on K joints \( J = \{ j_k \}_{k=1}^K \), called Linear Blend Skinning (LBS) [21]. For each 3D surface point \( X \) in the canonical space, given the target pose parameters \( R \) represented by relative rotations and the projection matrix \( P \) calculated by the camera external parameters, its projected location is:

\[
x = P \cdot \left( \sum_{k=1}^K w_k G_k(R, j_k) \right) \cdot X, \tag{2}
\]

where \( w_k \) is the skinning weight and \( G_k(R, j_k) \) is the affine transformation that transforms the \( k \)th joint from the canonical pose to the target pose [18].

Thanks to the development of human model fitting, we can estimate the pose \( R \), the corresponding \( G_k(R, j_k) \), and the projection \( P \) by fitting the SMPL to each frame [22]. Therefore, the main challenge is the unknown skinning weights \( w \), especially the 3D shape is inaccessible by now.

Skinning Weights Network (SKNet): To estimate the Linear Blend Skinning (LBS) without 3D shape, we extend the definition of LBS beyond body surface, and each \( X \) in the space is assigned skinning weights. Intuitively, since the regions close to the human body are highly correlated with the nearest body parts, we can place a mean-shape template in the canonical space and estimate
Figure 2: Overview of our framework. Given unconstrained images, the SKinning weights Network (SKNet) estimates the skinning weights, which are leveraged by the Surface Reconstruction Network (SRNet) to predict the occupancy field of a clothed human.

Figure 3: Nearest neighbor skinning weights (NN-Skin). (a) The skinning weights on the boundary of body parts are not continuous. (b) Surfaces may be ripped or adhered after deformation.

The skinning weights according to the closest point on the template, whose skinning weights are provided by the SMPL [25]. This Nearest Neighbor Skinning weights (NN-Skin) [18], as shown in Fig. 3(a), are not reliable due to two drawbacks. First, the skinning weights on the boundary of body parts are not continuous due to the nearest-neighbor criterion. After deformation, surfaces may be ripped or adhered due to the error on the NN matching, as shown in Fig. 3(b). Second, this error can be further amplified when the mean template does not resemble the ground-truth shape.

To address this problem, we propose the SKinning weights Network (SKNet) to learn an implicit skinning field [32] in the canonical space from multiple images. Given a 3D point \( X \), we build the SKNet to regress the skinning weights by:

\[
\mathbf{w}_\text{skin} = \text{Net}_{\text{skin}}(F(x_1,I_1),...,F(x_V,I_V),X),
\]

\[
x_o = P_v \ast \left( \sum_{k=1}^{K} w_{\text{nn}}^{kn}(R_v,j_k) \right) \ast X, \quad v = \{1, 2, ..., V\},
\]

where for each 3D point \( X \) in the canonical space, the Network \( \text{Net}_{\text{skin}}^{kn} \) takes the corresponding image feature \( F(x_o,I_o) \) in each frame and regresses the skinning weights through an MLP architecture. The 2D projection on each frame \( x_o \) is achieved as in Eqn. 2, where the NN-Skin \( w_{\text{nn}}^{kn} \) is employed. Particularly, the SKNet outputs \( K + 1 \) (\( K \) is the joint number) channels, where the first \( K \) channels are the skinning weights and the last channel holds the inside/outside probability as auxiliary supervision. The label is \((\mathbf{w}^*,0)\) for an inside point and \((0,0,...,1)\) for an outside point. The target skinning weights are provided by the new MVP-Human dataset, which is introduced in Section 4.2.

It is worth noting that, SKNet is naturally a cascade framework since the estimated skinning weights can be employed to improve the 2D projection, and then better skinning weights can be achieved through the next forward propagation. In our implementation, we only run SKNet once for efficiency. Compared to NN-Skin, SKNet enables more accurate 2D projection and avoids crack during avatar animation, which is validated in the experiments.

### 3.2 Surface Reconstruction via Adaptive Fusion

**Surface Reconstruction Network:** For surface reconstruction, we follow Eqn. 1 and use the occupancy function \( O \) to implicitly represent the 3D clothed human [18]:

\[
O = \{(o,X) : X \in \mathbb{R}^3, 0 \leq o \leq 1\},
\]

where \((o,X)\) denotes the occupancy value for one point \( X \) in the canonical space. In this paper, the \((o,X)\) is represented by a Surface Reconstruction Network (SRNet):

\[
o = \text{Net}_{\text{rec}}(F^I,F^S,X),
\]

where the network \( \text{Net}_{\text{rec}} \) takes the point \( X \), its multi-frame image feature \( F^I \), and a spatial feature \( F^S \) as inputs and estimates occupancy as the 3D shape.

**Image Feature:** After the estimation of SKNet, the 2D projections \( x_o \) for each frame \( I_o \) can be achieved by Eqn. 2, and the image feature can be extracted by bilinear sampling on the feature map of the image encoder. However, under unconstrained scenarios, the image features may not share the same importance since 1) the image feature may not describe the 3D point due to self-occlusion, and 2) the fitted SMPL may provide unreliable pose and view, leading to the sampling on the background. So directly averaging inferred
features [31] is improper. In this paper, we do not estimate blending weights by hand-crafted criteria but leverage the attention mechanism [36] for adaptive feature fusion.

Transformer [36] is originally proposed to capture the correlations across input sequences, and its self-attention mechanism is naturally extendable to our task. We employ a multi-head attention network as [11] to encode the relevance between features:

$$ F^I = \text{Attention}(t_1, ..., t_T), $$
$$ t_v = \text{Concat}(F(x_v, I_v), n_v), $$

where $F^I$ is the fused image feature, $t_v$ is the input token of the transformer, and each token is the concatenation of the retrieved image feature $F(x_v, I_v)$ and its visibility, represented by the surface normal $n_v$ on the fitted SMPL.

**Spatial Feature:** Recent methods [16, 18] have proved the effectiveness of the spatial feature that represents the geometric primitive of that point. In this work, we directly employ the estimated skinning weights as the spatial feature $F^S = w^{skin}(X)$ since it encodes the relationship of that point to each of the body landmarks. This mechanism avoids any external computation cost like hand-crafted features [18] and PointNet [16].

The training and testing of avatar reconstruction models depend on a sophisticated dataset equipped with multi-pose scans, multi-view images, and the strict T-pose shape for each subject, which is described as follows.

4 MULTI-POSE MULTI-VIEW 3D HUMAN DATASET

Reconstructing a 3D avatar from unconstrained frames is a novel problem. The training of ARWild relies on the 3D textured datasets of one subject in rich poses and its T-pose canonical mesh with skinning weights, which cannot be provided by existing datasets. Among existing datasets in Tab. 1, BUFF [46], CAPE [?], and THuman [48] are related datasets that provide multi-pose meshes for each subject, but they suffer from either limited subjects or low-quality 3D meshes. Besides, we wish to improve quantitative evaluation from rendered synthetic images to realistic inputs, requiring real-world multi-view and multi-pose images, and the corresponding ground-truth 3D shape. To this end, we create Multi-View multi-Pose 3D Human dataset (MVP-Human), a large 3D human dataset containing rich variations in poses and identities, together with the multi-view images for each subject.

4.1 Data Capture

**Capture Setting:** The capturing of the dataset took place in a custom-built multi-camera system. As shown in Fig. 4(a), the venue was 4m × 5m, and within it we obtained a capture space of 3m × 3m, where subjects were fully visible in all video cameras. Totally 8 capture components were placed around the area at equal 45° intervals to give full-body capture for a wide range of motions. Each component consisted of one Shenzhen D-VITEC1 RGB camera of 1080 × 720 resolution, 90° FOV, and 30 FPS for image collection, and one Wiiboox Reeye Pro 2X2 3D body scanner for 3D capture. All components were triggered in a synchronized manner. The outputs of the system were multi-view 1080 × 720 images (Fig. 4(b)) and 3D meshes with approximately 100,000 vertices, 2,000,000 faces, and 8400 × 8400 texture map. Besides, 3D landmarks with 62 points are manually labelled for each 3D mesh (Fig. 4(c)). More samples are demonstrated in the end of the paper.

**Subjects and Poses:** For the creation of the dataset, 400 distinctive actors with balanced gender and age (200 males and 200 females aged from 18 to 60) were recruited. Most of the subjects wore their own clothes, and some of them were asked to wear prepared clothes like common jack, pants, and track suits to maintain realism. To the best of our knowledge, MVP-Human is the largest 3D human dataset in terms of the number of subjects along with high-quality 3D body meshes and multi-view RGB images.

4.2 Skinning Weights Construction

To create the linear blend skinning weights as the supervision of SKNet, we optimize the canonical 3D model with the skinning weights for each subject following the recent SCANimate [32], shown in Fig. 4(d). Under the support of MVP-Human, where every subject has multiple scans in different poses with labeled 3D landmarks, we do not employ the original circle consistency loss and modify SCANimate in two aspects: 1) we directly optimize the chamfer errors brought by reposing, calculated by the distances between the reposed shape and the target-pose scan. 2) The reposing is guided by hand-labeled 3D landmarks rather than detected landmarks. The advanced SCANimate provides more reliable skinning weights, which are not only utilized as the target of SKNet but also used to repose the scanned T-pose shape to the strict T-pose as the target of SRNet. We also cut the edge in self-intersection regions according to [32] and fill the hole using smooth signed distance surface reconstruction [6].

4.3 Authorization

The MVP-human will be released to the public for academic use only, under the licence following the Restrictive Licence Template3, which is specially designed for privacy protection. All the actors have signed the authorization letters that approve us to release their 3D mesh and image data.

5 EXPERIMENTS

5.1 Implementation Details

The two sub-network follow the same MLP architecture [30] with the intermediate neuron dimensions of (1024, 512, 256, 128) and use the Stacked Hourglass [28] as the image encoder. The SKNet

---

1http://www.d-vitec.com
2https://www.wiiboox.net/3d-scanner-reeeye-2x.php

3https://library.unimelb.edu.au/Digital-Scholarship/restrictive-licence-template
Figure 4: Multi-View multi-Pose 3D Human dataset (MVP-Human). (a) Capture space and camera placement. (b) Captured multi-view images. (c) Textured 3D scan and labeled 3D landmarks. (d) Optimized canonical mesh and skinning weights which serve as the target of avatar reconstruction.

Figure 5: Specified 15 poses and canonical pose (strict T-pose) in MVP-Human. The specified poses consist of the clustered AMASS [26] poses and several common poses, such as T-pose, sitting, and walking.

5.2 Dataset

We split the MVP-Human into a training set of 350 subjects and a testing set of 50 subjects. For the training set, we create the rendering images of 3D meshes following [30], where 360 images are produced by rotating the camera around the vertical axis with intervals of 1°, generating 2,100,000 images. The ground-truth canonical shape and skinning weights are used for supervision. For the testing set, 4 images are randomly selected from the image collection of a subject as one testing sample, which is repeated 100 times to generate 5,000 testing samples. It is worth noting that, this testing set first enables the quantitative evaluation on real-world images. Besides MVP-Human, we also employ People-Snapshot [3] in qualitative evaluation, where the subjects are asked to rotate while holding an A-pose, whose scenario can be considered as an easier case of ours.
5.3 Comparisons

To the best of our knowledge, ARwild is the first method that enables clothed 3D avatar reconstruction from unconstrained RGB frames. To perform the comparison, we introduce a method solving a highly related task, and a modification of a state-of-the-art method.

VideoOpt (Video based Optimization) [3] takes a monocular RGB video where a subject rotates in an A-pose and generates the SMPL model with per-vertex offset by aligning rendered silhouettes to observations. This method can be generalized to the inputs without A-pose assumption but suffers from performance deterioration due to complicated silhouettes in the unconstrained environment.

Octopus [1] fits the SMPL+D model from semantic segmentation and 2D keypoints. Similar to VideoOpt, Octopus also employs the shape offsets to represent personal details, such as hair and wrinkles, but is much faster by employing a deep learning model.

MultiARCH is an extension of the state-of-the-art method ARCH [18]. The original ARCH learns to reconstruct a clothed avatar from a single image, which is extended by us to take multiple images, named MultiArch. The main difference between MultiArch and ARwild is that our method tries to estimate skinning weights rather than approximates that by nearest neighbor, and we fuse the image features by a sophisticated model to adapt to the complicated unconstrained environment.

For quantitative comparison, we evaluate the accuracy of the reconstructed canonical 3D shape on the testing set of MVP-Human (real images), with three metrics similar to [30], including the normal error, point-to-surface (P2S) distance, and Chamfer error. For fairness, the MultiArch is fine-tuned on the MVP-Human training set. As shown in Table 2, we achieve the best results.

For qualitative comparison, Fig. 6 shows the reconstructed shapes from rendering and real images of MVP-Human, and Fig. 7 shows the results in People-Snapshot, respectively. It can be seen that
Table 2: Quantitative comparisons of normal, P2S (cm), and Chamfer error (cm) on the MVP-Human, evaluated on the canonical shape. Lower values are better.

| Method       | Canonical Shape |          |          |          |
|--------------|-----------------|----------|----------|----------|
|              | Normal          | P2S      | Chamfer  |          |
| Octopus [1]  | 0.0266          | 2.2017   | 2.4854   |          |
| VideoOpt [3] | 0.0233          | 1.6590   | 1.9960   |          |
| MultiArch [18]| 0.0217         | 1.4208   | 1.8064   |          |
| Ours         | 0.0214          | 1.3418   | 1.7192   |          |

Figure 8: Shapes animated by the nearest neighbor skinning weights (top row) and the estimated skinning weights (bottom row). Please see the crotch.

Octopus [1] and VideoOpt [3], which attempt to learn SMPL offset, have difficulty in capturing fine-grained geometry due to the limited representation power of the shape space. MultiArch retains some distinctive shapes but suffers artifacts like discontinuous surfaces and distorted body parts, which come from the misaligned image features. In contrast, our method generates more realistic avatars with the estimated skinning weights and better image fusion. For further analysis, we show the results of a single-image-based method PIFu [30], seeing the poses are not well captured due to the depth ambiguity. Besides, our method shows good generalization by reconstructing pants in People-Snapshot even without the clothes in the training set.

We also evaluate the effectiveness of better skinning weights in animation. As shown in Fig. 8, compared with the common Nearest Neighbor Skinning weights (NN-Skin) [18], we learn continuous skinning weights which can articulate a mesh smoothly while retaining coherent geometric details.

5.4 Performance Analysis

Ablation Study: We evaluate our ARwild with several alternatives to assess the factors that contribute to the performance. First, with the fitted SMPL, our baseline employs NN-Skin to sample the image features across frames, which are concatenated to regress a pixel-aligned implicit function [30]. Second, the proposed SKNet is employed to refine the skinning weights. Third, the spatial features (Spatial) extracted from the implicit skinning fields are concatenated to the image features. Finally, the self-attention based feature fusion (FA) module is utilized to improve the robustness to inaccurate fitting and self-occlusion. As observed in Table 3, each proposed component improves the final performance.

Analysis on Input Number: Fig. 9 shows the 3D reconstruction errors with the growing number of inputs, from 1 to 8. We can see that the performance becomes better as the number of inputs increases and approximately saturates at about 4 inputs. For efficiency, the 4-way inputs are utilized in our method.

6 DISCUSSION

Conclusion: We explore a new task that learns a 3D human avatar from unconstrained frames. By introducing skinning weights network and surface reconstruction network, we are able to fuse the features of images captured in unconstrained environments. Besides, to support the new task, we create a large 3D human dataset MVP-Human with 6,000 3D scans, and 48,000 images for 400 subjects, which is the largest 3D human dataset equipped with multi-pose high-quality scans for each subject.

Limitations and Future Work: One prerequisite of our method is the pose and camera parameters provided by SMPL fitting. The parameters cannot be corrected in the current pipeline if the fitting fails. Therefore, the future work will introduce SMPL fitting in the pipeline, and refine pose and camera parameters together with 3D avatar reconstruction.

Table 3: Ablation study on MVP-human, evaluated by normal, P2S (cm), and Chamfer error (cm). The “SkinNet”, “Spatial”, and “FA” refer to the skinning weights network, spatial feature, and feature fusion module, respectively. The best results are highlighted. Lower values are better.

| Components | Metrics     |          |          |          |
|------------|-------------|----------|----------|----------|
| SKNet      | Normal      | 0.0217   | 1.4013   | 1.7961   |
|            | P2S         | 0.0232   | 1.3760   | 1.7595   |
|            | Chamfer     | 0.0215   | 1.3455   | 1.7243   |
| ✓          |             |          | ✓        | ✓        | 0.0214   | 1.3418   | 1.7192   |

Figure 9: Chamfer errors on MVP-human with different number of inputs. For fast evaluation, we utilize a smaller image encoder.
REFERENCES

[1] Thiemo Alldieck, Marcus Magnor, Bharat Lal Bhatnagar, Christian Theobalt, and Gerard Pons-Moll. 2019. Learning to reconstruct people in clothing from a single RGB camera. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 1175–1186.

[2] Thiemo Alldieck, Marcus Magnor, Weipeng Xu, Christian Theobalt, and Gerard Pons-Moll. 2018. Detailed human avatars from monocular video. In Proceedings of International Conference on 3D Vision (3DV). 98–109.

[3] Thiemo Alldieck, Marcus Magnor, Weipeng Xu, Christian Theobalt, and Gerard Pons-Moll. 2018. Video based reconstruction of 3d people models. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 8387–8397.

[4] Dragomir Anguelov, Praveen Srinivasan, Daphne Koller, Sebastian Thrun, Jim Rodgers, and James Davis. 2005. Shape: shape completion and animation of people. ACM Transactions on Graphics (TOG) 24, 3 (2005), 405–416.

[5] Bharat Lal Bhatnagar, Garvita Tiwari, Christian Theobalt, and Gerard Pons-Moll. 2019. Multi-garment net: Learning to dress 3d people from images. In Proceedings of the IEEE International Conference on Computer Vision (ICCV). 5420–5430.

[6] Fatih Calakli and Gabriel Taubin. 2011. SSD: Smooth signed distance surface reconstruction. Computer Graphics Forum (CGF) 30, 7 (2011), 1993–2002.

[7] Zhiqin Chen and Hao Zhang. 2019. Learning implicit fields for generative shape modeling. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 5939–5948.

[8] Christopher W. Cheng, Daren Xu, JunYoung Gwak, Kevin Chen, and Silvio Savarese. 2016. 3d-vtnet: A unified approach for single and multi-view 3d object reconstruction. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 625–644.

[9] Alvaro Collet, Ming Chuang, Pat Sweeney, Don Gillett, Dennis Evseev, David Calabrese, Hughes Hoppe, Adam Kirk, and Steve Sullivan. 2015. High-quality streamable free-viewpoint video. ACM Transactions on Graphics (TOG) 34, 4 (2015), 1–13.

[10] Edilion De Aguiar, Caesten Stollen, Christian Theobalt, Naveed Ahmad, Hans-Peter Seidel, and Sebastian Thrun. 2008. Appearance capture from sparse multi-view video. In Proceedings of the ACM SIGGRAPH. 1–10.

[11] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. 2021. An image is worth 16x16 words: Transformers for image recognition at scale. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).

[12] Vinayak Furukawa and Jean Ponce. 2009. Accurate, dense, and robust multi-view stereo. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) 32, 8 (2009), 1362–1376.

[13] Andrew Gibert, Marco Volino, John Collomosse, and Adrian Hilton. 2018. Volume metric performance capture from minimal camera viewports. In Proceedings of the European Conference on Computer Vision (ECCV). 566–581.

[14] Marc Habermann, Weipeng Xu, Michael Zollhoefer, Gerard Pons-Moll, and Christian Theobalt. 2019. Livecap: Real-time human performance capture from monocular video. ACM Transactions on Graphics (TOG) 38, 2 (2019), 1–17.

[15] Marc Habermann, Weipeng Xu, Michael Zollhoefer, Gerard Pons-Moll, and Christian Theobalt. 2020. Deepcap: Monocular human performance capture using weak supervision. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 5052–5063.

[16] Tong He, Yuanlu Xu, Shunsuke Saito, Stefano Soatto, and Tony Tung. 2021. ARCH++: Animation-ready clothed human reconstruction revisited. In Proceedings of the IEEE International Conference on Computer Vision (ICCV). 5422–5431.

[17] Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. 2020. NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. In ECCV.

[18] Alejandro Newell, Kaiyu Yang, and Jia Deng. 2016. Stack hourglass networks for human pose estimation. In Proceedings of the European Conference on Computer Vision (ECCV). 483–499.

[19] Gerard Pons-Moll, Javier Romero, Naureen Mahmood, and Michael J Black. 2015. Dyna: A model of dynamic human shape in motion. ACM Transactions on Graphics (TOG) 34, 4 (2015), 1–14.

[20] Shunsuke Saito, Zeng Huang, Ryota Natsume, Shigeo Morishima, Angjoo Kanazawa, and Hao Li. 2019. Pifu: Pixel-aligned implicit function for high-resolution clothed human digitization. In Proceedings of the IEEE International Conference on Computer Vision (ICCV). 2004–2134.

[21] Shunsuke Saito, Tomas Simon, Jason Saragih, and Hanbyul Joo. 2020. Pifhdf: Multi-level pixel-aligned implicit function for high-resolution 3d human digitization. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 84–93.

[22] Shunsuke Saito, Jinlong Yang, Qianli Ma, and Michael J Black. 2021. SCANimate: Weakly supervised learning of skinned clothed avatar networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2886–2897.

[23] Igor Sørensen, Miguel A Otaduy, and Dan Casas. 2019. Learning-based animation of cloth for virtual try-ons. Computer Graphics Forum (CGF) 38, 2 (2019), 355–366.

[24] Jonathan Starck and Adrian Hilton. 2007. Surface capture for performance-based animation. IEEE Computer Graphics and Applications 27, 3 (2007), 21–31.

[25] Guil Varelo, Duygu Ceylan, Bryan Russell, Jimei Yang, Ersin Yumer, Ivan Laptev, and Cordelia Schmid. 2018. Bodynet: Volumetric inference of 3d human body shapes. In Proceedings of the European Conference on Computer Vision (ECCV). 20–36.

[26] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Proceedings of Advances in Neural Information Processing Systems (NIPS). 5998–6008.

[27] Daniel Vlasic, Pieter Peers, Ilya Baran, Paul Debevec, Jovan Popović, Seymoun Rashtkieris, and Wojciech Matusik. 2009. Dynamic shape capture using multi-view photometric stereo. In Proceedings of the ACM SIGGRAPH Asia. 1–11.

[28] Michael Waschbüsch, Stephan Würmlin, Daniel Cotting, Filip Sadlo, and Markus Gross. 2005. Scalable 3D video of dynamic scenes. The Visual Computer 21, 8 (2005), 629–638.

[29] Chenglei Wu, Kiran Varanasi, Yebin Liu, Hans-Peter Seidel, and Christian Theobalt. 2011. Shading-based dynamic shape refinement from multi-view video under general illumination. In Proceedings of the IEEE International Conference on Computer Vision (ICCV). 11046–11056.

[30] Chenglei Wu, Kiran Varanasi, and Christian Theobalt. 2012. Full body performance capture under uncontrolled and varying illumination: A shading-based approach. In Proceedings of the European Conference on Computer Vision (ECCV). 737–770.

[31] Weipeng Xu, Avishek Chatterjee, Michael Zollhöfer, Helge Rhodin, Dushyanth Mehta, Hans-Peter Seidel, and Christian Theobalt. 2018. Monoperfcap: Human performance capture from monocular video. ACM Transactions on Graphics (TOG) 37, 2 (2018), 1–15.

[32] Jinhong Yang, Jean-Sébastien Franco, Franck Hérot-Wheeler, and Stefanie Wuhrer. 2016. Estimation of Human Body Shape in Motion with Wide Clothing. In Proceedings of the IEEE International Conference on Computer Vision (ICCV). 439–454.

[33] Tao Yu, Zerong Zheng, Kaiwen Guo, Pengpeng Liu, Qionghai Dai, and Yebin Liu. 2021. Function4D: Real-time human volumetric capture from very sparse consumer RGBD sensors. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 5746–5756.

[34] Chao Zang, Sergio Pujades, Michael J Black, and Gerard Pons-Moll. 2017. Detailed, accurate, human shape estimation from clothed 3D scan sequences. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 4191–4199.

[35] Chao Zang, Sergio Pujades, Michael J Black, and Gerard Pons-Moll. 2017. Detailed, accurate, human shape estimation from clothed 3D scan sequences. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 4191–4209.

MVP-Human Dataset for 3D Human Avatar Reconstruction from Unconstrained Frames
[46] Chao Zhang, Sergi Pujades, Michael J. Black, and Gerard Pons-Moll. 2017. Detailed, accurate, human shape estimation from clothed 3D scan sequences. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 4191–4200.

[47] Yang Zheng, Ruizhi Shao, Yuxiang Zhang, Tao Yu, Zerong Zheng, Qionghai Dai, and Yebin Liu. 2021. DeepMultiCap: Performance capture of multiple characters using sparse multiview cameras. Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2021).

[48] Zerong Zheng, Tao Yu, Yixuan Wei, Qionghai Dai, and Yebin Liu. 2019. Deephuman: 3d human reconstruction from a single image. In Proceedings of the IEEE International Conference on Computer Vision (ICCV). 7739–7749.

[49] C Lawrence Zitnick, Sing Bing Kang, Matthew Uyttendaele, Simon Winder, and Richard Szeliski. 2004. High-quality video view interpolation using a layered representation. ACM Transactions on Graphics (TOG) 23, 3 (2004), 600–608.
7  FULL DATA OF EACH SUBJECT
We show all the collected data for two subjects in Fig. 10. Each subject is captured in 15 poses, each of which has: 1) The 3D mesh with approximately 100,000 vertices, 2,000,000 faces and 8400 × 8400 texture map (first column). 2) The manually annotated 3D landmarks with 62 points (second column). 3) The 1080 × 720 images captured in 8 views at equal 45° intervals to give full-body capture (other columns). There are 400 volunteers participating in the collection, proving 6,000 3D scans and 48,000 images in total. Besides, we also attach a raw 3D human mesh in obj format for demonstration.
Figure 10: The collected data for two subjects in MVP-Human. Each subject is captured in 15 poses, and each pose has a 3D textured scan (first column), annotated 3D landmarks (second column), and multi-view images (other columns). The images are cropped for better visualization.