Dual-Space NeRF:
Learning Animatable Avatars and Scene Lighting in Separate Spaces

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Abstract

Modeling the human body in a canonical space is a common practice for capturing and animation. But when involving the neural radiance field (NeRF), learning a static NeRF in the canonical space is not enough because the lighting of the body changes when the person moves even though the scene lighting is constant. Previous methods alleviate the inconsistency of lighting by learning a per-frame embedding, but this operation does not generalize to unseen poses. Given that the lighting condition is static in the world space while the human body is consistent in the canonical space, we propose a dual-space NeRF that models the scene lighting and the human body with two MLPs in two separate spaces. To bridge these two spaces, previous methods mostly rely on the linear blend skinning (LBS) algorithm. However, the blending weights for LBS of a dynamic neural field are intractable and thus are usually memorized with another MLP, which does not generalize to novel poses. Although it is possible to borrow the blending weights of a parametric mesh such as SMPL, the interpolation operation introduces more artifacts. In this paper, we propose to use the barycentric mapping, which can directly generalize to unseen poses and surprisingly achieves superior results than LBS with neural blending weights. Quantitative and qualitative results on the Human3.6M and the ZJU-MoCap datasets show the effectiveness of our method. Our code is available at: https://github.com/zyhbili/Dual-Space-NeRF.

1. Introduction

Human body reconstruction and rendering have long been an active research topic. Multi-view videos are especially suitable for this task because they record not only the appearance but also the movements and deformation of a person. Classic reconstruction and rendering techniques show limited image realism due to the complexity of decoupling the geometry, material and lighting from images. However, the recently proposed neural radiance field (NeRF) [14] proves it possible to represent a static scene with an MLP without explicitly modeling the above factors. Several recent works [20, 9, 19, 15, 24, 26, 27, 8] have adapted NeRF onto human body reconstruction and animation, but challenges remain in the following aspects:

Recent methods that model the human body with NeRF [14] mostly learn the human body in a canonical space, but the lighting inconsistency in the canonical space lacks exploration [20, 9, 19, 15, 24]. When learning a NeRF in the canonical space, we assume the appearance of a person is consistent across varied body poses. But the fact is when a person moves, a point in the canonical space comes to a different place in the world space, resulting in a change...
of the lighting condition. This means that merely modeling the appearance of a person in the canonical space is not enough. Therefore, we propose to model the scene lighting with another MLP in the world space, where the scene lighting is assumed to be static. The lighting MLP takes in a point position, a normal vector, and a view direction in the world space, and outputs a lightness coefficient that adjusts the brightness of the point.

Different from NeRF [14] that only depends on the point position and the viewing direction, our lighting MLP also takes in a normal vector, still due to the complexity of dynamic scenes. For a static scene, the surface normal can be uniquely determined by the point position, while for our setting, the surface normal may change when the subject moves. Unlike IDR [28] that models the lighting condition and the appearance of an object with one appearance MLP, our method learns the two factors with separate MLPs in different spaces to realize correct lighting under unseen poses. Also, our lighting MLP only predicts a scalar coefficient to rescale the color from the body MLP instead of directly predicting a color to prevent overfitting.

To bridge the world space and the canonical space, the key is building pixel-level correspondences across views and frames. A stream of methods bind points on 3D skeletons [15, 24] based on the assumption of local rigidity. Another stream of methods incorporates geometric priors characterized by anchoring points onto SMPL [11], a parametric human body model. Neural Body [20] binds features onto SMPL’s vertices and diffuses them into the space before volumetric rendering. It produces realistic novel views of the training sequence but degrades on novel poses. Animatable NeRF [19] resolves novel-pose synthesis by mapping observed points into a canonical space with inverse linear blend skinning (LBS). Since the LBS weight of a spatial point varies for different poses, Animatable NeRF [19] learns a neural blending weight network conditioned on the pose, which requires additional training for novel poses.

To avoid learning the volatile LBS weights, we seek a pose-independent local position representation that generalizes to novel poses easily. Specifically, we propose a barycentric mapping (BM) as follows. For a point in the space, we first project it onto its closest face on the fitted SMPL mesh. Then we describe this point by the barycentric coordinates of its projected point and its signed height from the face. Finally, its corresponding point in the canonical space is uniquely determined. Note that NPMs [16] leverages a similar barycentric mapping to obtain pseudo ground truths to train a unidirectional deformation field. While in our method, we extend BM to support vector transformation and use it bidirectionally, transforming a point position from the world space to the canonical space and warping a surface normal from the canonical space to the world space. By this barycentric mapping, the body MLP and the lighting MLP are bridged. BM is parameter-free, enabling pose generalization without additional input or network fine-tuning. Though the parameter-free method seems to have inferior expressiveness, our experiments show its comparable ability on two datasets and clear advantages under challenging poses. It is flexible since it anchors a point on the edge vectors of a face, allowing local deformation along with the face. It also avoids the artifacts of inverse LBS caused by blending weighting interpolation (Fig. 7).

Another challenge of this task is the existence of random variations such as clothing wrinkles. These variations are neither fully determined by the body pose nor consistent across frames, making it harder to learn a stable canonical radiance field. Neural Actor [9] uses the ground-truth texture map to relieve the ambiguity in training images but requires a separate image generation network to infer texture maps from normal maps for testing. Motivated by SCANimate [22], to model the pose-dependent deformation, our model is conditioned on the pose parameters. Besides, per-frame latent embeddings are used to capture the random variations. According to our experiments, the union of these components is sufficient to represent vivid deformations along with pose changes with no need for an extra deformation network.

Our contributions can be summarized as follow:

- To ensure the lighting correctness under unseen poses, we propose dual-space NeRF, which models the static scene lighting in the world space and the human body in the canonical space.
- We propose to use the barycentric mapping to build correspondences between two spaces and validate its comparable expressiveness and superior generalization ability under extreme poses.
- We show the effectiveness and interpretability of our method with quantitative and qualitative results on the Human3.6M [7] and the ZJU-MoCap [20] datasets.

2. Related Work

3D human reconstruction. As a popular 3D articulated human model, SMPL [11] learns a template mesh from 3D scans and deforms the mesh with the linear blend skinning (LBS) algorithm. The mesh-based 3D human model is easy to manipulate but limited to a fixed topology. Therefore, neural implicit functions are adopted to model a 3D avatar that can be animated by SMPL [22, 3, 4, 13], LEAP [13], SCANimate et al. [22], and SNARF [3] learn the human body in a canonical space and articulate the body with neural blending weights. NASA [4] is a part-based method that binds an implicit function on each bone. These methods use 3D data as the input and only account the shape of the human body.

Dynamic neural radiance field. Neural radiance fields
Figure 2: The pipeline of our method. Given a point $p^w$ in the world space, we use the barycentric mapping to warp a point $p^w$ from the world space into the canonical space to query the body properties. In the canonical space, we compute the surface normal $n^w$ and warp it back to obtain the normal vector $n^c$ in the world space. We learn a Body MLP to model a human body in the canonical space and a Lighting MLP to capture the lighting condition in the world space. Finally, we render an image with volumetric rendering.

Human body animation with NeRF. To animate a NeRF of a human body, a straightforward solution is incorporating 3D human priors. Peng et al. [20] use a set of latent code to encode the local geometry and appearance of the human body and bind them onto SMPL [11] vertices. Liu et al. [9] introduce Neural Actor, animating NeRF with blending weights sampled from the nearest vertex of SMPL. Additionally, an image translation network is used to infer texture maps to provide residual deformations and appearance details for novel poses. AniNeRF [19] learns a neural blending weight field to learn the LBS weights for each particular pose. Since the blending weight field varies with poses, AniNeRF relies on a per-frame latent vector as a condition for training poses and requires fine-tuning for novel poses. Xu et al. [27] learn NeRF upon imGHUM [1], a statistical human body model represented by neural implicit functions.

3. A Revisit of NeRF

NeRF [14] represents a scene by density $\sigma$ and color $c$ at each spatial point $p$. To render an image in an arbitrary view, $\sigma$ and $c$ are accumulated along viewing rays. Formally, we denote a viewing ray emitted from the optical center of a camera through a given pixel on the image plane by $r(m) = \alpha + md$, then an approximation of the pixel color is

$$\hat{C}(r) = \mathcal{R}(r, c, \sigma) = \sum_{k=1}^{K} T(m_k) \sigma(m_k) \delta_k c(m_k),$$

where $\mathcal{R}(r, c, \sigma)$ is the volumetric rendering of the color $c$ with the density $\sigma$; $\{m_k\}_{k=1}^{K}$ is a set of discretely sampled points between the near and the far plane of the camera; $\delta_k = m_{k+1} - m_k$ is the distance between the current sampling point and the next one; $T(m_k) = \exp \left(-\sum_{k'=1}^{k-1} \sigma(m_{k'}) \delta_{k'} \right)$, and $\alpha(x) = 1 - \exp(-x)$. NeRF learns a radiance field with an MLP in the form of

$$[\sigma(m), c(m)] = f_\theta(\gamma_p(r(m)), \gamma_d(d)), \quad \text{(2)}$$

where $\theta$ is the model parameter, $\gamma_p(\cdot)$ and $\gamma_d(\cdot)$ are fixed positional encoding functions for positions and directions.

The network parameters are optimized by the loss

$$\mathcal{L} = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} \left\| \mathbf{C}(r_{ij}) - \hat{\mathbf{C}}(r_{ij}) \right\|_2^2, \quad \text{(3)}$$

where $N$ is the number of images, $M$ is the number of rays in each image, and $r_{ij}$ is the $j^{th}$ ray in the $i^{th}$ image.
4. Method

Our method learns to reconstruct a person from synchronized multi-view video frames and animates the subject with novel poses. This is achieved by learning a canonical neural radiance field [14] of a human body in X-pose. This canonical radiance field is anchored to SMPL [11] so that we can animate the radiance field by manipulating SMPL. In Fig. 2, we show the pipeline of our method with barycentric mapping (Sec. 4.1) and dual-space NeRF (Sec. 4.2). The dual-space NeRF includes two networks: a Body MLP (Sec. 4.2.1) to model a human body in the canonical space and a Lighting MLP (Sec. 4.2.2) to capture the location-dependent lighting in the world space. And the barycentric mapping bridges the canonical space and the world space.

4.1. Barycentric Mapping

Considering the sparsity of views and the ambiguity caused by smooth regions, it is tough to learn robust correspondences across frames purely with images. Therefore, we adopt SMPL [11] as a geometric prior of the human body by anchoring spatial points on the faces of SMPL.

4.1.1 Position mapping

For a point \( p_w \) in the world space (Fig. 3), we first determine its closest face \( F_i^w \) by measuring its distances to the mean of vertex positions of each face. Then, we set up a local description of the point \( p_w \) by \((u, v, h)\), where \((u, v)\) is the barycentric coordinate of the projection of \( p_w \) on the face \( F_i^w \), and \( h \) is the signed distance from \( F_i^w \). Based on the corresponding face of \( F_i^w \) in the canonical space, i.e., \( F_i^c \), we can compute the corresponding point of \( p_w \) as:

\[
p^c = o^c + uu^c + vv^c + h \frac{u^c \times v^c}{\|u^c \times v^c\|},
\]

where \( o^c \) is the first vertex of the face \( F_i^c \), \( u^c \) and \( v^c \) are two edge vectors of \( F_i^c \) starting from the vertex \( o^c \). Note that the mapping can be conducted in an inverse direction.

4.1.2 Direction mapping

Based on the position mapping, we can bridge direction vectors between spaces, also in a differentiable manner. For the example in Fig. 3, we first represent the direction vector \( n^w \) by its starting point \( p^c \) and its ending point \( p^w_c = p^c + n^c \). Then we apply the position mapping described above to get the corresponding positions in the world space, i.e., \( p^w \) and \( p^w_c \). Finally, the warped direction vector in the world space can be obtained by:

\[
n^w = \frac{p^w - p^w_c}{\|p^w - p^w_c\|}.
\]

![Figure 3: The barycentric mapping of positions and directions. For a point \( p^w \) in the world space, we first find its closest face \( F_i^w \), whose corresponding face in the canonical space is \( F_i^c \). Then, we represent \( p^w \) as the barycentric coordinate \((u, v)\) of its projection on \( F_i^w \) and its signed distance \( h \) from \( F_i^w \). Finally, we compute the counterpart of \( p^w \) in the canonical space, i.e., \( p^c \), with the same local representation upon \( F_i^c \). The barycentric mapping can also be used to transform direction vectors.](image)

4.2. Dual-Space NeRF

NeRF [14] astonishes the community for its high rendering realism, especially for the view-dependent visual effects. Most importantly, NeRF is formulated as a function of merely a point position \( p \) and a viewing direction \( d \). Physically, the shading of a point also depends on the lighting condition and the surface normal, but NeRF omits them because they can be fully determined by the point position for a static scene.

However, for animatable human reconstruction and animation, the lighting condition is static only in the world space while the body shape and the surface normal is consistent only in the canonical space. Therefore, we have to learn a Body MLP and a Lighting MLP in separate spaces.

4.2.1 Body MLP

Given a point position \( p^w \) in the world space (also called the observed space), we use the barycentric mapping (Sec. 4.1.1) to obtain its corresponding point in the canonical space, i.e., \( p^c \), which is the main input of the Body MLP. Motivated by SCANimate [22], we encode the quaternion matrix of the joints of SMPL with a tiny MLP and get the pose feature \( J \). To prevent artifacts and blur in the results, we also learn a latent embedding \( \ell_i \in \mathbb{R}^3 \) for each video frame \( i \) to model the random variations that cannot be fully determined by the body pose.

Formally, we feed the canonical point position \( p^c \), pose features \( J \), and latent embedding \( \ell_i \) into the Body MLP to predict density \( \sigma \) and texture \( t \in \mathbb{R}^3 \). Here, Eq. (2) is reformulated as:

\[
[\sigma, t] = f_{\theta_1}(\gamma_p(p^c), J, \ell_i).
\]
For the Body MLP, density $\sigma$ models the static shape and texture $t$ models the true color of a human body in X-pose, both independent of the viewing direction. Moreover, the surface normal at the position $\mathbf{p}^c$ can be obtained by the normalized gradient of density $\sigma$ with respect to $\mathbf{p}^c$ [23, 2]:

$$n^c = -\frac{\nabla \sigma}{\|\nabla \sigma\|}. \tag{7}$$

4.2.2 Lighting MLP

To illustrate the necessity of a separate Lighting MLP, we consider a point $\mathbf{p}^c$ on a hand of a subject in the canonical space. When the subject waves the hand, the corresponding location of $\mathbf{p}^c$ in the world space moves, resulting in a change of the lighting condition. Therefore, from the perspective of the point $\mathbf{p}^c$, the lighting condition varies with the body pose. Although the per-frame (or per-pose) lighting embeddings used by previous methods [19, 17] do help relieve the inconsistency of lighting in the training frames, they cannot generalize to novel poses. In contrast, we learn a Lighting MLP in the world space, making the lighting condition independent of the body pose.

Concretely, we use the Lighting MLP to predict a lightness coefficient

$$s = f_{\Theta_s}(\mathbf{p}^w, d^w, n^w), \tag{8}$$

where $\mathbf{p}^w$ is the point position, $d^w$ is the viewing direction, and $n^w$ is the surface normal, all in the world space. During ray casting and point sampling, $\mathbf{p}^w$ and $d^w$ are directly available while the surface normal $n^w$ is not. To obtain $n^w$, we first use the barycentric mapping (Sec. 4.1.1) to find the corresponding point of $\mathbf{p}^w$ in the canonical space, i.e., $\mathbf{p}^c$, then compute the surface normal of $\mathbf{p}^c$, i.e., $n^c$, finally map $n^c$ back to the world space also with the barycentric mapping (Sec. 4.1.2). The lightness coefficient $s$ is meant to scale the lightness of the texture $t$ for shading with the color

$$c = st, \tag{9}$$

and the final result is obtained by volumetric rendering with the density $\sigma$ and the color $c$. Here, we model the lighting condition with simply a lightness coefficient instead of a color vector or more complex models because the task is highly under-constrained, and suppressing the expressiveness of the Lighting MLP helps prevent overfitting (Fig. 8).

4.3. Implementation Details

We apply the neutral SMPL [11] model for body mesh fitting. Personalized shape parameters are used for each subject. The X-pose is chosen as the canonical pose. Our network consists of 2 parts: the Body MLP is an 8-layers MLP with a shortcut connected to the fifth layer, and the Lighting MLP is a 4-layers MLP. We use a 3-layer MLP to learn the pose feature $J$. Hidden layers are activated by ReLU. The per-frame embeddings are initialized with Gaussian distribution ($\mathcal{N}(0, 1)$). We use the Adam optimizer to train our network for 200 epochs. We set the learning rate to 0.0005 and exponentially downscale it until the last epoch to 10 times lower. Weight decay is not used. We use a batch size of 1 with 5000 rays per batch. We sample 64 points on each ray. To accelerate training and inference, we abandon the coarse-to-fine strategy [14, 20, 19]. Instead, we adopt the geometry-guided strategy [9, 27], which produces a tighter bound. Since we have instance-level human-parsing masks, we ensure that 5 percent of rays are sampled around the face in each iteration, and the other rays are randomly sampled in the 2D bounding box. All experiments are conducted on a GeForce RTX 2080 Ti GPU and take around two days to converge.

5. Experiments

5.1. Settings

Datasets. ZJU-MoCap [20] is a multi-view dataset containing 9 performers captured by 21 synchronized cameras. It provides estimated SMPL [11] parameters and instance-level human-parsing masks generated by an established method [5]. We follow the experimental settings of Neural Body [20] and AniNeRF [19]. Images corresponding to four uniformly distributed cameras are used for training and the rest for evaluation. We conduct experiments on 8 performers. Human3.6M [7] contains four-view videos with human poses collected by a marker-based motion capture system. Images corresponding to three views are used for training and one for evaluation. We use the same protocol as Neural Body [20] to generate SMPL [11] parameters and masks.

Metrics. We adopt three metrics to evaluate the rendering quality, including PSNR, SSIM, and LPIPS [29]. PSNR is a pixel-wise metric based on the mean squared error, which is sensitive to noises and random variations. SSIM measures the structural similarity based on luminance, contrast, and structure comparisons. LPIPS [29] measures the perceptual distance between an image pair in a deep feature space. Since most pixels in the datasets belong to the background, we calculate PSNR and SSIM only within the 2D foreground mask, which is obtained by projecting the 3D bounding box on to the image plane.

5.2. Image Synthesis in Novel Poses

Baselines. Since we focus on the generalization ability of the model under novel poses, we compare our method with two state-of-the-art methods [20, 19] on novel pose synthesis. For results on novel view synthesis, please refer to our supplementary material. Note that we cannot compare with some recent works [9, 27] since the official code
As shown in Tab. 1 and Tab. 2, our method achieves the best PSNR and SSIM scores compared to two strong baselines. Since previous works [30, 10, 9] show that higher PSNR and SSIM scores do not guarantee better visual quality of images, we report LPIPS as a perceptual measurement, on which our method also shows advantages. According to Fig. 4 and Fig. 5, our method produces fewer artifacts than AniNeRF [19], indicating a better correspondences across frames. Meanwhile, the lighting conditions in our results are closer to the ground truths and the details are easier to recognize thanks to the reasonable decoupling of body properties and the environmental lighting. As shown in Fig. 4 and Fig. 5, Neural Body [20] tends to produce wrong body structures on Human3.6M when an unseen pose is far from the seen ones in the training set. While, our method produces visually pleasing results under novel poses, demonstrating the robustness of the barycentric mapping and the correctness of our lighting model.
Comparison on extreme pose synthesis. Since the difference between the training and the test poses in a dataset may not be large enough, we compare the methods on a challenging pose sequence from the AMASS [12] database. As shown in Fig. 6, Neural Body produces corrupted limbs and faces, which show the limitation of the convolution-based solution. AniNeRF makes artifacts and blurs due to the instability of the spatially interpolated LBS weights and the poor generalization ability of the neural blending weights. Our method renders sharp images with clear details and realistic lighting thanks to the stable correspondences and reasonable decoupling of body properties and the environmental lighting. Please refer to our supplementary video for animated results.

5.3. Ablation Studies

To verify the effectiveness of our main components, we conduct ablation studies on the “Twirl” sequence of ZJU-MoCap [20] in terms of novel pose and novel view synthesis. All models are trained for the same number of epochs (100) for a fair comparison.

Barycentric mapping. To validate the virtue of the barycentric mapping, we replace it with the inverse LBS algorithm. For the blending weights, we follow the strategy of AniNeRF [19], which interpolates the blending weights from nearby SMPL vertices. The second row of Tab. 3 shows the clear superiority of the barycentric mapping, especially on novel poses. In the visual comparison (Fig. 7), inverse LBS produces artifacts around movement-frequent places like armpits and feet, while the barycentric mapping still performs well.
Figure 7: Visual comparison between the barycentric mapping and inverse LBS. Inverse LBS with interpolated blending weights produces artifacts near movement-frequent places like armpits and feet while the barycentric mapping renders clear results.

Figure 8: Ablation study of the Lighting MLP. We test with an alternative design of Lighting MLP that directly predicts RGB values instead of predicting the lightness coefficient for texture scaling. However, the Lighting MLP that directly predicts colors tends to overfit the training frames and produces distorted colors on the novel pose.

|                 | PSNR↑ | SSIM↑ | LPIPS↓ |
|-----------------|-------|-------|--------|
|                 | View  | Pose  | View   | Pose  |
| Full model      | 31.090| 24.216| 0.970  | 0.911 | 0.023  | 0.044 |
| Replace BM with inverse LBS | 30.758| 23.301| 0.968  | 0.895 | 0.026  | 0.055 |
| w/o Lighting MLP | 30.696| 23.465| 0.967  | 0.906 | 0.027  | 0.049 |
| Lighting MLP (predicting color) | 31.270| 23.570| 0.971  | 0.905 | 0.019  | 0.047 |

Table 3: Ablation studies. “View” refers to novel view synthesis, and “Pose” refers to novel pose synthesis. “BM” means the barycentric mapping. Bold values are the best scores, and underlined values are the second best.

6. Conclusion

In this paper, we focus on the generalization problem of human body reconstruction and animation. We propose to model the human body and the lighting condition in separate spaces. To bridge the canonical space and the world space, we propose the barycentric mapping, which helps us to transform point positions and surface normals of a human body between the two spaces, enabling rendering in the world space with body properties from the canonical space. Most importantly, the barycentric mapping can directly generalize to novel poses without additional input or network training. Thanks to the reasonable decoupling of body properties and lighting conditions, we obtain clear improvements upon two strong baselines.

7. Limitations and Potential Impacts

Our method uses SMPL [11] as a proxy to build connections between the world space and the canonical space. Therefore, it strongly relies on an accurate SMPL fitting. In scenarios where SMPL parameters cannot be precisely obtained, our method is likely to fail. Also, our approach does not model long-range dependencies and thus is unable to deal with a performer in a long dress. Our work reconstructs the appearances of subjects and animates them with public video datasets. Currently, the rendering realism is far from fooling people, but attention should be paid to future versions of related technologies for potential misusing.

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