

GHNeRF: Learning Generalizable Human Features with Efficient Neural Radiance Fields

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Abstract

Recent advances in Neural Radiance Fields (NeRF) have demonstrated promising results in 3D scene representations, including 3D human representations. However, these representations often lack crucial information on the underlying human pose and structure, which is crucial for AR/VR applications and games. In this paper, we introduce a novel approach, termed GHNeRF, designed to address these limitations by learning 2D/3D joint locations of human subjects with NeRF representation. GHNeRF uses a pre-trained 2D encoder streamlined to extract essential human features from 2D images, which are then incorporated into the NeRF framework in order to encode human biomechanic features. This allows our network to simultaneously learn biomechanic features, such as joint locations, along with human geometry and texture. To assess the effectiveness of our method, we conduct a comprehensive comparison with state-of-the-art human NeRF techniques and joint estimation algorithms. Our results show that GHNeRF can achieve state-of-the-art results in near real-time. The project website: arnabdey.co/ghnerf.github.io.

1. Introduction

Developing a realistic virtual human model is pivotal for achieving natural experiences in Augmented Reality (AR) / Virtual Reality (VR) applications and interactive games. Moreover, creating custom photo-realistic virtual character from a sparse set of 2D images is one of the core challenges for AR/VR applications. Traditionally, this process has involved the use of elaborate multiview capture systems, which incorporate extensive camera arrays and body markers [15, 34], to create human models with the underlying skeleton structure. These conventional methods predominantly utilize mesh representations, which are inherently

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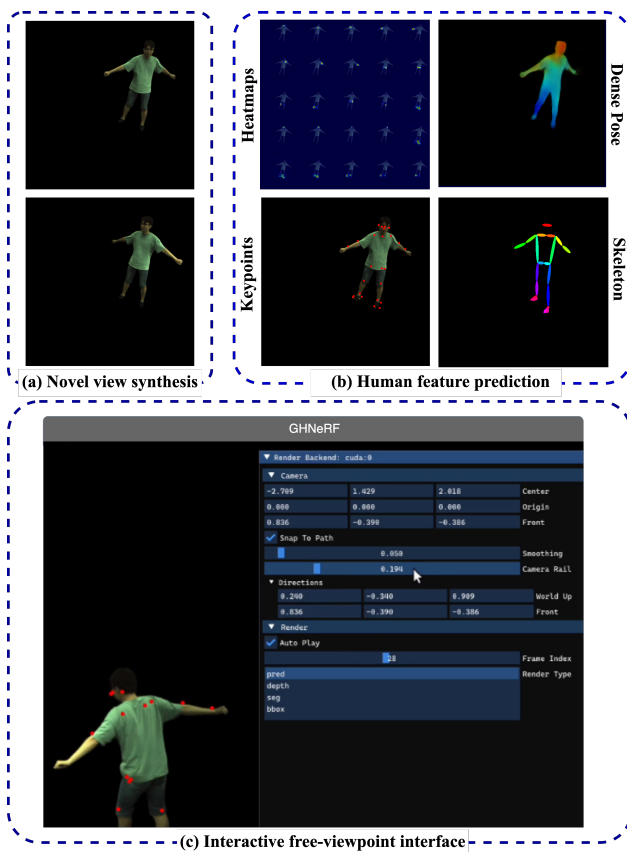


Figure 1. In this work we propose **GHNeRF**, it can simultaneously learn both neural radiance fields and human features from sparse images. (a) shows high quality novel-view renderings. (b) shows generalizable human features (keypoints, dense pose, etc.) estimated by GHNeRF. (c) present interactive tool to render free-viewpoint videos of novel-view and human features.

constrained in terms of resolution and quality. The underlying structures in these models are typically represented with parametric Skinned Multi-Person Linear (SMPL) models [22] derived from body marker positioning.

Recent advancements in Neural Radiance Fields (NeRF) have demonstrated remarkable potential in generating photorealistic virtual human avatars from mere 2D images [14, 21, 37]. However, existing NeRF-based approaches fall short in providing critical structural biomechanical attributes, crucial for various applications such as AR/VR, 3D animation, human performance analysis, and the medical field. To bridge this gap, we introduce a Generalizable Human feature NeRF (GHNeRF), an end-to-end framework for learning generalizable human NeRF with biomechanic features. Human biomechanics refers to the study of human movement focusing musculoskeletal system, comprising bones, muscles, ligaments, and joints [24]. Within the scope of this paper, the term 'biomechanical features' specifically refers to the skeleton and joints integral to this system. Deviating from previous methods such as PixelNeRF [45], which used a 2D encoder to learn generalizable NeRF for view synthesis, our approach utilizes 2D deep feature extractors to simultaneously learn human features with generalizable NeRF models. Here, we demonstrate that it is possible to learn 3D human features from 2D images using the NeRF architecture. The GHNeRF predicts human features, such as heatmaps, facilitating 2D/3D joint estimation for novel views, which are applied to various downstream applications. We highlight that while we focussed on the *joint prediction*, the architecture can be used to learn other biomechanic properties, such as dense pose and body part segmentation.

Our methodology adopts 2D encoders similar to previous methods [43, 45] aimed at generating pixel-aligned human features from images. For this purpose, we compare two types of encoder inspired by previous state-of-the-art pose estimation algorithms. GHNeRF determines heatmaps corresponding to each joint, along with the color and volume density for each 3D query point. The input for the MLP are pixel-aligned features from encoder, as well as view direction. The heatmaps are generated using volume rendering similar to rendering color in NeRF. We use an efficient and generalizable NeRF architecture as a backbone similar to the one presented by Lin *et al.* [21] that allows for near real-time inference.

To evaluate GHNeRF, we present the result of keypoint estimation tasks using two popular datasets. To our knowledge, our method is the first to provide human biomechanic features from NeRF. Our contributions are summarized as follows.

- We introduce GHNeRF, a novel generalizable NeRF architecture capable of accurately estimating 2D/3D human keypoints.
- GHNeRF demonstrates the ability not only to predict human keypoints but also to estimate complex human features, such as dense poses. This capability can also be achieved through the distillation of SoTA pose estimation

algorithms.

- We provide a generalizable approach for predicting human feature, photometric, and geometric representations from 2D sparse images, applicable in interactive, real-time applications.
- We conduct extensive experimental analyses across various types of human images using two distinct datasets to validate the applicability and versatility of GHNeRF.

2. Related works

The proposed GHNeRF uses sparse multiview images of different humans to learn a generalizable NeRF representation that can also produce a consistent 3D human feature without any prior supervision during inference time. In the following, work related to this research will be discussed.

2.1. NeRF for 3D representation

In recent years, the NeRF-based method has gained significant popularity for the visual quality of 3D scene representations. NeRF [26] represents 3D scenes using MLP by mapping 3D coordinates and 2D view directions to density and color. The original paper [26] and the following research work [1, 2, 25, 30, 35] showed the effectiveness of the neural field compared to other classical methods for representing 3D and 4D scenes. The works [7, 21, 28, 44] address the long training and inference time of the NeRF by using faster sampling techniques, voxel representation, and hash encoding. Another limitation of NeRF-based methods is that they are scene specific, PixelNeRF [45] showed that NeRF models can be generalized by conditioned NeRF on input image. More recently, FeatureNeRF [43] learned deep features using pre-trained vision foundation models for downstream applications such as semantic segmentation and key point transfer. Several methods [19, 38, 50] extended the NeRF's ability by learning scene properties, for example, semantic segmentation of the scene. However, most of the previous work focuses on scene features, such as segmentation. Our work differs from them by learning human biomechanic features with NeRF.

2.2. NeRF for human representation

In recent research, Hu *et al.* [14] generated generalizable and animatable human NeRF models from a single input image. Although they achieved great results, their method relies on the SMPL parameters as input along with image, which is difficult to obtain in a real-world scenario. Similarly, GM-NeRF [5] used the SMPL model to learn a generalizable human NeRF model. Several works [16, 41, 46] generated NeRF models of human in canonical T-pose (example SMPL [23] T-pose) then map it to a posed space. Similarly, [17, 33, 37, 40] uses pre-existing skeleton data or pose estimator or information from the SMPL model [23]

to reconstruct novel views or novel poses. As an example, A-NeRF [37] employs off-the-shelf pose estimators to initialize their model, while our generalizable method does not require any pose initialization. In this paper, we predict human biomechanic features, such as joint information, directly from 2D images without any supervision.

2.3. Human pose estimation

Human pose estimation has been a long-standing problem in computer vision for decades. Most state-of-the-art approaches for 2D human pose estimation employ 2D CNN architectures for a single image in a strongly supervised setting [3, 6, 9, 13, 18, 29, 39]. For 3D pose estimation, [27, 36] focus on end-to-end reconstruction by directly estimating 3D poses from RGB images without intermediate supervision. [48] applies GCNs for regression tasks, especially 2D to 3D human pose regression. [31] demonstrates that 3D poses in video can be effectively estimated with a fully convolutional model based on dilated TCNs over 2D keypoint sequences. Among these methods, [27, 29, 36, 39] have first incorporated a person detector, followed by the estimation of the joints and then the computation of the pose for each person – however the detection speed is proportional to the number of people in the image. Bottom-up methods such as [3, 6, 18] detect joints via heatmaps and associate body parts, but struggle with occluded or truncated body parts. Our approach integrates an encoder with NeRF to directly estimate heatmaps from 3D NeRF features, enhancing accuracy in predicting non-visible regions in 2D.

3. Method

We present GHNeRF, a unified framework for learning generalizable human features with the efficient NeRF architecture. First, we present an introduction to NeRF and its generalizable variants. Then in Section 3.2, we outline the feature extraction process and explain how to learn human features with NeRF in Section 3.3. Finally, we provide details of keypoint extraction in Section 3.4.

3.1. Preliminaries

Neural Radiance Fields (NeRF) learn 3D scene representations using a multilayer perceptron (MLP). The input to the MLP consists of 3D coordinates $x = (x, y, z)$ and the view direction $\mathbf{d} = (\theta, \phi)$. The outputs are color, $c = (r, g, b)$ and density (σ). It can be represented as: $F(x, \mathbf{d}) \rightarrow (c, \sigma)$ then volume rendering is used to generate the final pixel colors from the output. To predict images, first, 3D points are sampled along the rays $r(t) = o + t\mathbf{d}$ passing through each pixel, with o the camera center and \mathbf{d} the direction of the ray. The color and density of the samples are predicted using an MLP as discussed before. The final color of the

pixel C of a camera ray $r(t) = o + t\mathbf{d}$ can be calculated as:

$$C(r) = \int_{t_n}^{t_f} T(t)\tau(r(t))c(r(t), \mathbf{d})dt, \quad (1)$$

where $T(t) = \exp(-\int_{t_n}^t \tau(r(s))ds)$. The function $T(t)$ denotes the accumulated transmittance along the ray from t_n to t , t_n and t_f is near and far bound of the ray. In practice, the color $\widehat{C}(r)$ is estimated by obtaining discrete samples along the ray, and the integral is approximated using numerical quadrature techniques.

In case of generalizable NeRF, the NeRF models are conditioned on the input image I :

$$\begin{aligned} \sigma(x, I) &= g_\sigma(x, f(I)_{\pi(x)}) \\ c(x, \mathbf{d}, I) &= g_c(x, \mathbf{d}, f(I)_{\pi(x)}), \end{aligned} \quad (2)$$

where g_σ and g_c are two MLPs that predict density and color, f is an image encoder and π is a projection function that projects x into the image plane using the known pose and intrinsic. The image passes through an encoder to generate features, then for each query point x , the corresponding pixel-aligned features [45] $f(I)_{\pi(x)}$ are concatenated with the positional encoding of the point before inputting into the NeRF model. Similarly, ENeRF [21] extracts multiscale image features from a CNN-based encoder, and then the encodings are also used as input and to create a cost volume. Given the cost volume, a 3D CNN generates a depth probability volume, which is used to predict the depth probability of a pixel. ENeRF uses depth probabilities to sample points close to the surface, resulting in fewer samples and faster training and inference time.

3.2. Feature extraction

We propose a new architecture to generalize human NeRF with the underlying biomechanic features. The original NeRF model predicts the color c and the density σ for each query point $x = (x, y, z)$, while the most generalizable NeRF models are conditioned on input images. We take inspiration from previous generalizable methods [21, 43, 45], and we use two different encoders: one to generate a human feature and the other for multiscale image features similar to [21]. Each query point is projected on the input images, and then the pixel-aligned image features from each image are combined using a pooling operator [21] that is denoted as $f_{img} = \psi(f_1, \dots, f_N)$ where f_N represents the feature of the N^{th} image. Multiscale features are also used to generate voxel-aligned features similar to [21] denoted by f_{voxel} . Subsequently, we introduce a second encoder to encode human features. It has been demonstrated that human features extracted from Transformer-based encoder [8] pre-trained on ImageNet are more effective in generalizing human pose estimation [42, 49] compared to CNN-based features [10, 36]. In this work, we compare both types of

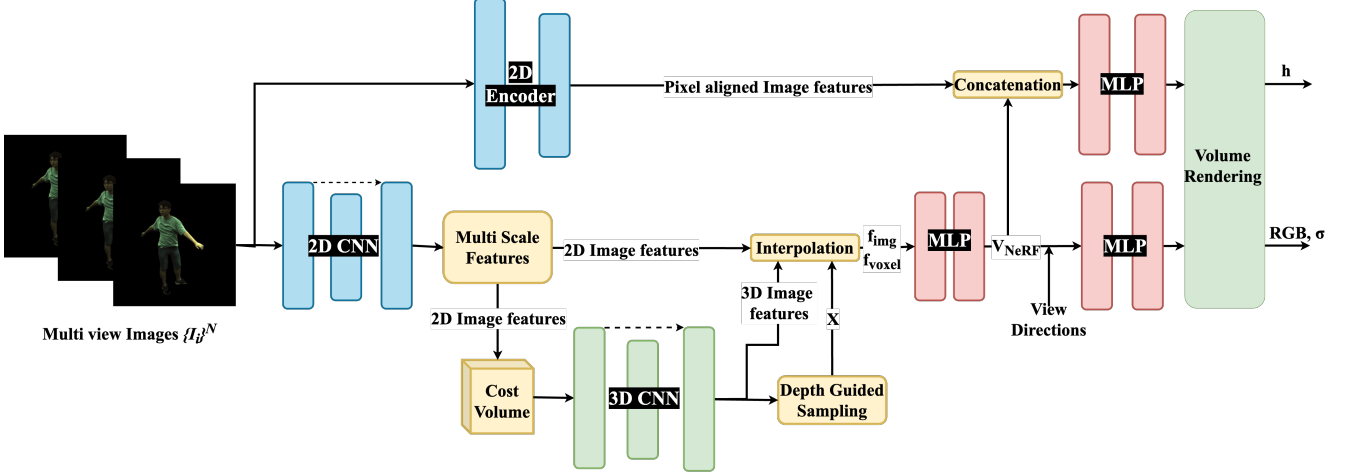


Figure 2. **Overview of the GHNeRF pipeline:** Given an input image I , human features f_h and multi-resolution image features f_{img} can be extracted using a 2D image encoder and a 2D CNN respectively. Subsequently, f_{img} is used to form a cost volume for depth prediction. The predicted depth is used for depth-guided sampling to reduce the number of samples along the ray. For each 3D sample point x along the ray, we combine image and voxel features to input an MLP g_{NeRF} , generating the intermediate NeRF feature V_{NeRF} . Finally, the intermediate NeRF feature V_{NeRF} and the human feature f_h are concatenated and fed into a smaller MLP g_h to produce heatmaps. Furthermore, V_{NeRF} and the view direction \mathbf{d} are combined in another MLP g_c to derive color c . The final pixel color and heatmaps are generated using volume rendering technique.

encoders and select the vision transformer encoder [8] to extract more effective features for human pose estimation. Specifically, we use a pre-trained vision transformer to extract a higher-dimension feature vector \mathbf{h} following [4]. For each query point x , we combine all pixel-aligned human features $f_h = \psi(\mathbf{h}_1, \dots, \mathbf{h}_N)$ from input images with a pooling operator.

3.3. Learning human features with NeRF

Generalizable NeRF models predict color c and σ for any query points, GHNeRF extends the generalizable NeRF models to predict additional features, in this case human joint locations. Although we have extracted features from images, we still need to incorporate them with NeRF, in order to output 3D consistent human features from NeRF. In this work, we learn intermediate NeRF features $V_{NeRF}(x, I)$ similar to [43]. Then we use a number of small MLPs to predict other outputs from the intermediate NeRF feature:

$$\begin{aligned}
 V_{NeRF}(x, I) &= g_{NeRF}(f_{img}, f_{voxel}) \\
 \sigma(x, I) &= g_{\sigma}(V_{NeRF}(x, I)) \\
 c(x, \mathbf{d}, I) &= g_c(V_{NeRF}(x, I), \mathbf{d}) \\
 h(x, I) &= g_h(V_{NeRF}(x, I), f_h).
 \end{aligned} \tag{3}$$

The color is predicted using a smaller MLP g_c that takes the intermediate NeRF input feature V_{NeRF} and the view direction as input. An additional branch predicts human joint locations as heatmaps h from NeRF features. We take inter-

mediate NeRF features before outputting color and density and concatenate with human feature f_h and pass it through a smaller MLP g_h that outputs heatmaps as feature vector $h \in \mathbb{R}^J$ where J is the number of joints. We can aggregate these feature vectors along the rays similar to color using volume rendering:

$$\hat{H}(r) = \sum_{i=1}^N T_i (1 - \exp(-\tau_i \delta_i)) h_i, \tag{4}$$

where $h_i = g_h(V_{NeRF}(x, I), f_h)$ and $V_{NeRF}(x, I)$ denotes intermediate NeRF features. The network is optimizing using a set of human images in a random pose and appearance with known camera parameters. The proposed method is optimized using photometric and feature loss. The photometric loss l_{col} is calculated using the mean squared error between the predicted and the ground-truth color. We also add perceptual loss l_{perc} to image patches similar to [21]. Feature loss l_{heat} is the mean square error between the predicted feature and the ground-truth feature in this case heatmaps. The final loss function can be represented as:

$$l = l_{col} + \lambda_p l_{perc} + \lambda_h l_{heat}$$

where λ_p, λ_h weighting coefficients. During training, when ground truth features are not present, our method represents a student network, which can learn heatmaps through distillation of advanced heatmap-based pose estimation algorithms. The pose estimation algorithm [3] acts as a teacher

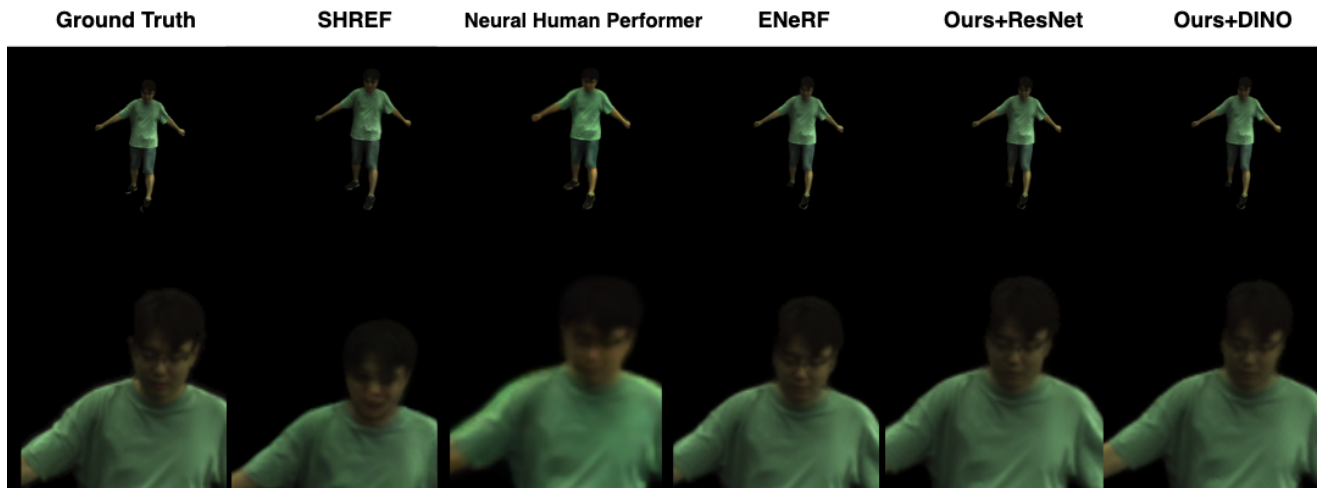


Figure 3. Qualitative comparison of generalization results on ZJU_MoCap unseen test sequence.

network with the ability to predict heatmaps, thus guiding our student network in its heatmap prediction task.

3.4. Keypoints extraction

The 2D keypoint locations are estimated from the predicted heatmaps generated by NeRF. We calculate the 2D keypoints in a similar way to OpenPose [3]. A Gaussian filter is applied to the heatmaps, and then each channel is converted to a binary map by applying a threshold. Connected regions are created from binary maps, and the peak value within that region is calculated. The pixel with the peak value is then outputted as the 2D keypoint. To extract the 3D keypoints, we query sample points from a 3D volume around the subject and extract a volumetric heatmap. The 3D keypoints are calculated from the volumetric heatmap in a similar way as in the 2D keypoints.

4. Experimental Results

We conducted a thorough evaluation of the ability of our model to learn human features, particularly to estimate human joint locations. We carried out extensive experiments on two distinct datasets and compared our results with those of other leading human NeRF techniques.

4.1. Experimental Setting

Datasets: We trained our model to be applicable to various types of human image using two different datasets, namely ZJU_MoCap [32] and RenderPeople [14]. Both datasets are focused on humans and contain dynamic sequences of different individuals performing various activities. The ZJU_MoCap dataset contains real images, while the RenderPeople dataset contains simulated images. ZJU_MoCap includes 9 dynamic sequences (images, masks, camera pa-

rameters, and 2D/3D joint locations) of 9 different individuals performing 9 different actions. We randomly divided 6 sequences for training and 2 for testing and removed one sequence due to missing frame data. For RenderPeople, we randomly chose 440 sequences for training and 60 for testing.

Baseline: We predominantly compare GHNeRF with other methods based on dynamic human NeRF. Although such methods are generalizable, none are capable of generating human features. We have extended ENeRF[21] to output heatmaps by adding an additional output branch and reported its performance as a baseline for the joint estimation task.

Implementation details: We employ ENeRF as the base generalizable NeRF architecture due to its efficiency and generalizability, and proceeded to modify it to generate generalizable human features. We employed two distinct encoders, ResNet [12] and DINO [4], in accordance with the most recent pose estimation techniques. In our experiments, we set the number of input source views to 2. We implemented our generalizable NeRF model using PyTorch. We trained the models with an RTX 3090 GPUs, using the Adam optimizer with an initial learning rate of $5e^{-4}$. We halved the learning rate every 50k iterations, and the model generally converged after about 200k iterations, taking about 18 hours. The weights of different losses are $\lambda_h = 0.5$ and $\lambda_p = 0.01$. For more information on the network architecture and other implementation details, see the Supplementary Material.

Metrics: We employed five different metrics to evaluate the predicted RGB image, heatmaps, and joint estimation quality. Peak Signal-to-Noise Ratio (PSNR in dB): To compare the quality of the RGB reconstruction, the higher is better; Structural Similarity Index (SSIM): To compare im-

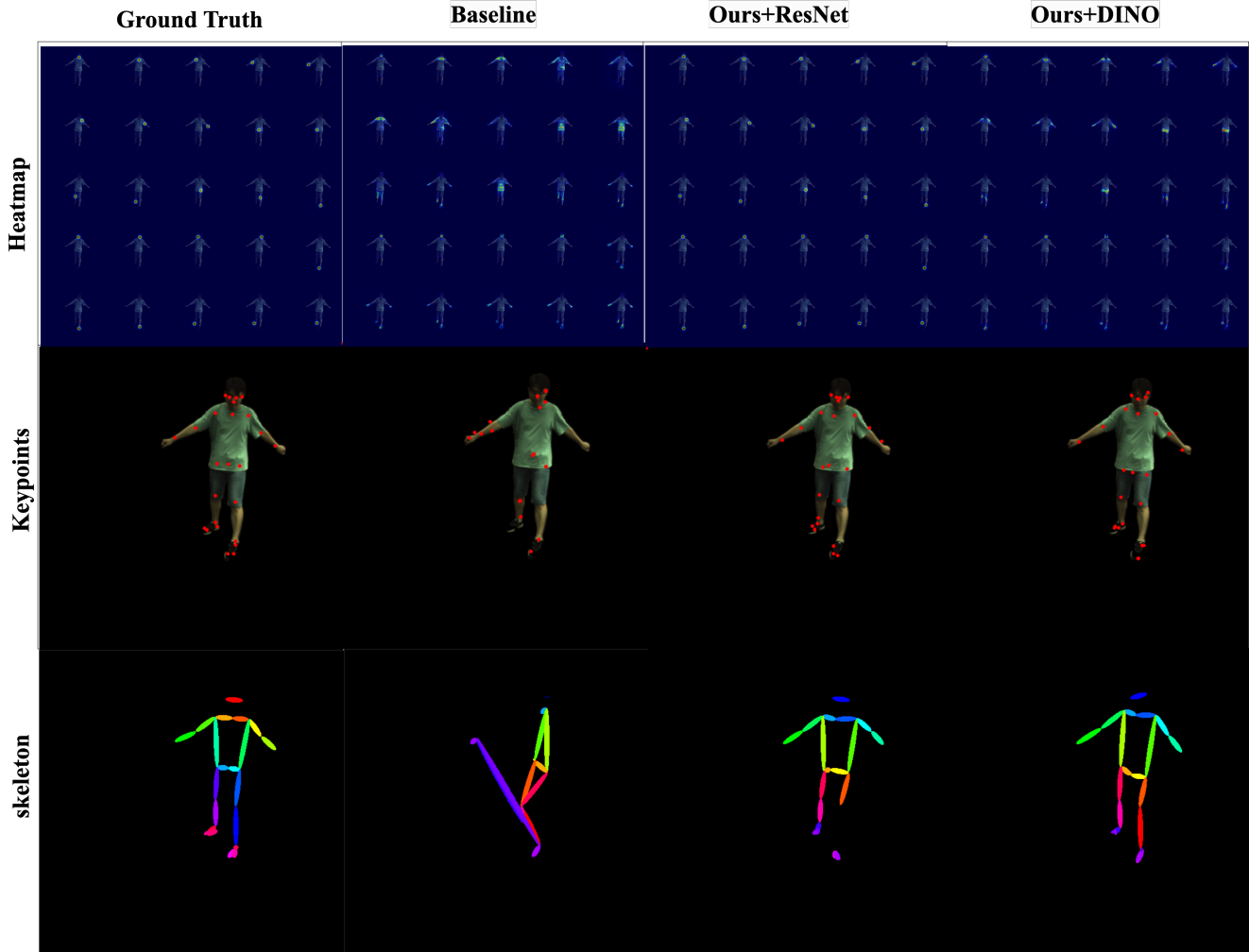


Figure 4. Qualitative result of keypoint estimation on ZJU_MoCap dataset.

age quality in the reconstructed image, the higher is better; Learned Perceptual Image Patch Similarity (LPIPS) [47]: the distance between the patches of the image, the lower means that the patches are more similar; Mean Squared Error (MSE): Mean squared distance between ground truth heatmap and predicted heatmap, lower the better; Percentage of correct keypoints (PCK): Measures whether the predicted keypoints and the true joint are within a certain distance threshold. We use PCK@0.2: Distance between the predicted and true joint $< 0.2 \times$ torso diameter.

4.2. Performance on novel view synthesis and joint estimation

We compared our method with recent generalizable NeRF-based methods on dynamic scenes, Table: 1 lists the quantitative result on ZJU_MoCap dataset, which shows our method achieves state-of-the-art performance, while additionally estimating human joints. To establish a baseline,

we incorporated an additional heatmap branch into ENeRF. The experiments show that our method maintains the same level of performance in novel-view synthesis compared to state-of-the-art ENeRF [21] but performs significantly better in joint estimation compared to the baseline ENeRF. It also demonstrates that the human feature encoder offers essential information about human features to more accurately estimate heatmaps crucial for better joint estimation. Figure 3 illustrates the qualitative outcomes of various approaches in ZJU_MoCap dataset. Our technique demonstrates highly competitive results in novel-view synthesis and notably outperforms SHREF [14] and the Neural Human Performer [20] in preserving intricate details..

In Figure 4, we have presented qualitative results of human joint estimation task using the ZJU_MoCap dataset. We generated 25 distinct heatmaps representing different keypoints, with each keypoint being highlighted by red markers. We evaluated our approach using two different

Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	MSE \downarrow	PCK \uparrow
SHERF [14]	26.37	0.918	0.1023	-	-
Neural Human Performer [20]	25.76	0.906	0.148	-	-
ENeRF [21]	31.48	0.965	0.0494	-	-
ENeRF+Heatmap	31.48	0.965	0.050	0.0005	0.438
Ours+ResNet	31.20	0.963	0.054	0.0004	0.573
Ours+DINO	31.61	0.966	0.050	0.0003	0.691

Table 1. Quantitative comparison of generalization (unseen test set) on the ZJU_MoCap dataset, evaluating all methods at 512×512 resolution. For these experiments, we adhered to the default configurations of SHERF, Neural Human Performer, and ENeRF.

Dataset	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	MSE \downarrow	PCK \uparrow
ZJU_MoCap+Res	31.20	0.963	0.054	0.0004	0.573
ZJU_MoCap+DINO	31.61	0.966	0.050	0.0003	0.691
RenderPeople+Res	34.44	0.992	0.0131	0.0012	0.521
RenderPeople+DINO	34.75	0.992	0.0131	0.0005	0.502

Table 2. Quantitative results of the proposed method in different datasets. The results represent generalizable performance on unseen scenes from the test set. Both datasets are evaluated on images with resolution 512×512 .

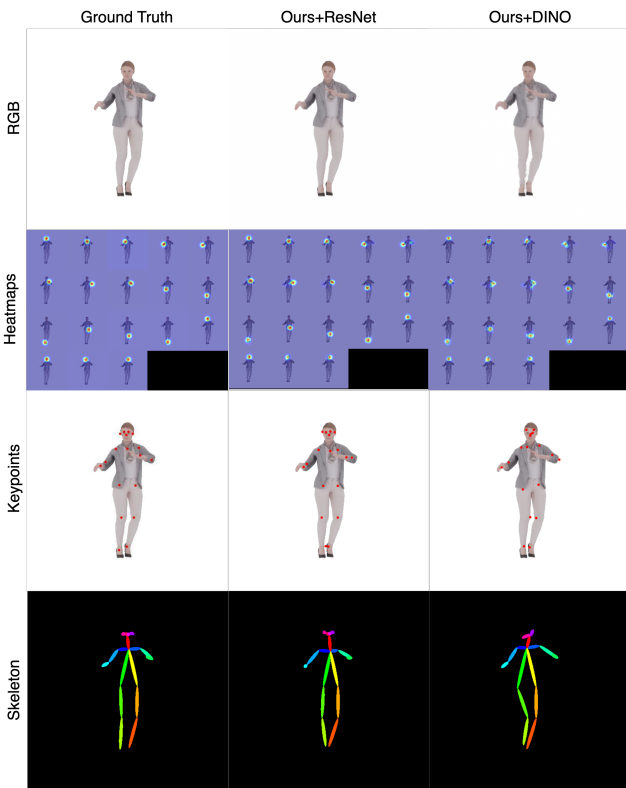


Figure 5. Qualitative result of keypoint estimation on RenderPeople dataset.

types of dataset and reported quantitative results in Table 2. In both datasets, the DINO features showed superior per-

	Alpha Pose [10]	Open Pose [3]	GHNeRF +Res	GHNeRF +DINO
PCK \uparrow	0.647	0.632	0.573	0.691
MSE \downarrow	0.0013	0.0015	0.0004	0.0003

Table 3. Quantitative results of keypoint estimation compare to other pose estimation algorithms. We used same ZJU_MoCap test set images of resolution 512×512 to evaluate all three methods.

formance in predicting human features as heatmaps. We validate our approach using both real images and simulated images to demonstrate its robustness. Qualitative results of novel-view synthesis and joint estimation on RenderPeople dataset are presented in Figure 5. To gauge the effectiveness of our proposed method for joint estimation, we compared it with other state-of-the-art pose estimation algorithms and presented the findings in Table 3. Our approach with both ResNet and DINO encoder outperform Alpha Pose and Open Pose, achieving superior PCK and MSE scores. More details, experiments, and results are provided in the Supplementary Material.

Dataset	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	MSE \downarrow
ZJU_MoCap+Res	37.22	0.9885	0.0190	0.0039
ZJU_MoCap+DINO	36.51	0.9877	0.0205	0.0019

Table 4. Quantitative results of the dense pose estimation on ZJU_MoCap dataset. Here, MSE is the mean squared error between the predicted and estimated Continuous Surface Embeddings for Dense Pose.

4.3. Performance on dense human pose estimation

In order to showcase GHNeRF’s ability to learn other generalizable human features, we conducted additional experiments to predict dense pose. During training, we use DensePose [11] to generate ground-truth Continuous Surface Embeddings of ZJU_MoCap dataset. We used the same architecture without any modification to learn Continuous Surface Embeddings as human feature from 2D images, which can be used for dense pose estimation. We provide the quan-

titative results in Table 4. The results show that our model can effectively estimate dense pose with different encoders, *e.g.*, ResNet, and DINO, and we find that the DINO encoder performs better compared to ResNet for dense pose estimation similar to joint estimation task. The qualitative results of the estimation of dense pose are presented in Fig. 6. Both qualitative and quantitative findings demonstrate that GHNeRF is capable of learning other generalizable human features beyond just keypoint estimation. This experiment validates our assumption that GHNeRF can learn different human features using the same model architecture.

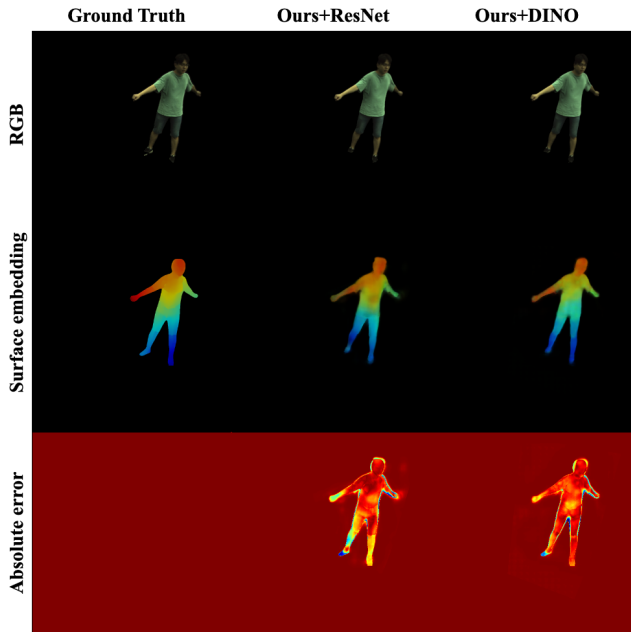


Figure 6. Qualitative result of dense pose estimation on ZJU_MoCap dataset. The absolute error demonstrates the effectiveness of our model with DINO feature in learning dense pose.

4.4. Rendering speed

Inference time of various methods in novel view synthesis and keypoint estimation is illustrated in Table 5. We compared the proposed method with the baseline approach (ENeRF with an extra heatmap branch). While the utilization of the DINO encoder may result in longer inference times, it surpasses other methods by providing superior joint estimation. It may be feasible to attain faster inference time by employing a custom Visual Transformer-based encoder and optimization while maintaining the same level of performance. All experiments were performed on a single RTX 3090 GPU using the PyTorch implementation. We are confident that by optimizing and fine-tuning the code, the rendering time can be improved in the future.

Method	FPS
ENeRF	31.10
ENeRF+Heatmap	27.81
Ours+ResNet18	11.22
Ours+ResNet34	10.49
Ours+DINO	4.08

Table 5. Average rendering speed in FPS(Frame per second). ENeRF+Heatmap represent the baseline method.

4.5. Ablation study

In Table 6, we present the impact of different encoder architectures on the human joint estimation task. We have chosen two different encoder architectures inspired by previous state-of-the-art pose estimation algorithms, namely ResNet [12] and DINO [4]. Both methods produced comparable results in terms of visual quality, but DINO outperformed significantly in the joint estimation task.

Encoder	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	MSE \downarrow	PCK \uparrow
ResNet34 <i>Pre</i> [12]	31.53	0.965	0.049	0.0005	0.454
ResNet34 <i>Fine</i> [12]	31.20	0.963	0.054	0.0004	0.573
DINO <i>Pre</i> [4]	31.28	0.964	0.051	0.0003	0.682
DINO <i>Fine</i> [4]	31.61	0.966	0.050	0.0003	0.691

Table 6. Ablation study for keypoint estimation. We show a comparison between different types of encoder for keypoint estimation task. We evaluated both models on ZJU_MoCap dataset. *Pre* represents Pre-trained and *Fine* denotes Finetune during the training.

5. Conclusion

In this paper, we present GHNeRF an end-to-end framework to learn generalizable NeRF to estimate human biomechanic features from 2D images. Through extensive experiments, we have established that our approach can be successfully applied in a variety of settings. We addressed the shortcomings of underlying structure in previous NeRF based methods for humans. The proposed method utilizes an encoder to predict human features using NeRF. In this paper, we focus on estimating human keypoints, and we have also shown how it can be extended to other human features by estimating dense pose. Although our method can estimate human features efficiently, it still has the following shortcomings: 1. It only works in scenes with a single human and it cannot handle multiple humans. 2. The proposed method is limited to humans and does not apply to other animals and articulated objects, which can be a future perspective to learn more general underlying structure.

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