

GeoMan: Temporally Consistent Human Geometry Estimation using Image-to-Video Diffusion

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<https://research.nvidia.com/labs/dair/geoman>

Abstract

Estimating accurate and temporally consistent 3D human geometry from videos is a challenging problem in computer vision. Existing methods, primarily optimized for single images, often suffer from temporal inconsistencies and fail to capture fine-grained dynamic details. To address these limitations, we present GeoMan, a novel architecture designed to produce accurate and temporally consistent depth and normal estimations from monocular human videos. GeoMan addresses two key challenges: the scarcity of high-quality 4D training data and the need for metric depth estimation to accurately model human size. To overcome the first challenge, GeoMan employs an image-based model to estimate depth and normals for the first frame of a video, which then conditions a video diffusion model, reframing video geometry estimation task as an image-to-video generation problem. This design offloads the heavy lifting of geometric estimation to the image model and simplifies the video model’s role to focus on intricate details while using priors learned from large-scale video datasets. Consequently, GeoMan improves temporal consistency and generalizability while requiring minimal 4D training data. To address the challenge of accurate human size estimation, we introduce a root-relative depth representation that retains critical human-scale details and is easier to be estimated from monocular inputs, overcoming the limitations of traditional affine-invariant and metric depth representations. GeoMan achieves state-of-the-art performance in both qualitative and quantitative evaluations, demonstrating its effectiveness in overcoming longstanding challenges in 3D human geometry estimation from videos.

1. Introduction

Estimating human 3D geometry [44, 45, 56] from images or videos has enabled numerous applications in digital human and virtual reality. While significant progress [27, 58, 59] has been made, most methods [17, 28, 29] focus on single-

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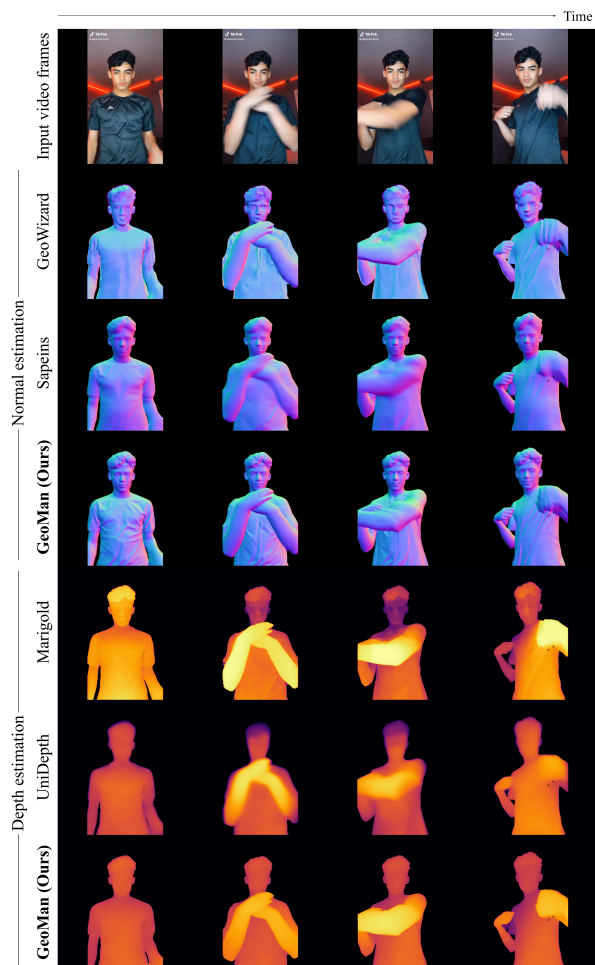


Figure 1. GeoMan provides accurate and temporally stable geometric predictions for human videos, surpassing existing methods.

image geometric estimation. When applied to videos, these methods often struggle with temporal inconsistency, causing visible flickering artifacts and missing fine dynamic details such as subtle facial deformations, clothing wrinkles, and hair movements. These details are crucial for applications involving human motion, as shown in Fig. 1 This work aims to estimate highly accurate and temporally consistent depth and normal from monocular human videos.

This is a highly challenging task that presents two difficulties. First, the scarcity of high-quality 4D data poses a significant challenge to training accurate geometry estimation models. Recent works [14, 28] address this limitation by repurposing text-to-image diffusion models for image-based geometry estimation. These methods modify the diffusion denoiser architecture to intake both the input image and geometric information, followed by fine-tuning on image-geometry pairs. Extending these approaches to video geometry estimation introduces additional challenges due to the higher dimensionality and complexity of videos. While some methods [23, 57] have explored adapting video diffusion models to video depth estimation, they often require a substantial amount of high-quality video-depth sequences. For instance, DepthCrafter [23] curates a large-scale dataset including approximately 200K real and synthetic video-depth pairs. Consequently, this strategy cannot be naively extended to human video geometry estimation, as high-quality 4D human data is difficult to collect. The second challenge lies in selecting an appropriate depth representation. Depth estimation from monocular inputs is inherently ambiguous. Most methods resort to predicting affine-invariant depth, which normalizes the depth map using the minimum and maximum depth value for each image or video. While affine-invariant depth simplifies the learning objective and encourages the models to focus on local geometric details, it sacrifices essential size and scale information, particularly for human subjects, resulting in distorted 3D geometry and temporal flickering as presented in Fig. 5. Recent methods [3, 5, 22, 37] have attempted to predict metric depth to address these issues; however, they often do so at the expense of spatial details.

To address these challenges, we introduce *GeoMan*, a novel approach for temporal consistent and accurate depth and normal estimation from monocular human videos. To reduce dependency on 4D training data, we decompose the complex video geometry estimation task into image geometry estimation and image-to-video synthesis. This allows us to maximally exploit the prior in image-to-video diffusion models by introducing minimal changes to the diffusion model architecture. As a result, we maintain its powerful representation capabilities and generalization ability while adapting it for our specific task with limited 4D training data. To achieve this, we first train an image-based model to estimate depth and normal maps of static images. This model is then used to predict geometric information of the first frame of a video, which serves as conditioning input for an image-to-video diffusion model. The video model subsequently infers temporally consistent geometric information for the entire video. Furthermore, GeoMan unifies depth and normal estimation by leveraging a single video diffusion model. This is achieved by simply switching the conditioning image, enabling simultane-

ous training for both modalities (depth and normal) and enhancing generalization across diverse scenarios. Second, to preserve human scale information in depth estimation, GeoMan introduces a root-relative depth representation tailored for human-centric geometry estimation. This representation retains essential metric-scale details while discarding only global translation, facilitating accurate local geometric details estimation. When necessary, absolute translation can be efficiently recovered using state-of-the-art human pose estimation models (e.g., [54, 62]), enabling absolute metric depth estimation. Unlike conventional per-frame or per-video normalization techniques that hinder metric depth recovery and degrade temporal stability by computing independent scale factors per frame or per video, our approach enables consistent and stable depth estimation over time. Our contributions are:

- We propose GeoMan, which repurposes image-to-video diffusion models for temporally consistent depth and normal estimation in human videos, even when trained on limited data.
- We introduce a root-relative depth representation that preserves critical human size information, enabling metric depth estimation and 3D reconstruction.
- Extensive evaluations show that GeoMan surpasses baselines in accuracy and temporal stability, while effectively generalizing to in-the-wild human videos.

2. Related Works

Image-Based Geometry Estimation. Image-based depth and normal estimation has advanced significantly in recent years. By leveraging mixed datasets and powerful diffusion models [4], state-of-the-art approaches such as MiDaS [40], Depth-Anything [58, 59], Marigold [28], and GeoWizard [14] achieve high accuracy and impressive generalization. In parallel, a line of research has focused on human-centric geometry estimation. This approach utilizes either implicit surface regression [1, 16, 44, 45] or parametric body models (e.g., SMPL [36]) [24, 33, 55, 56, 63, 69]. Recently, HDNet [27] proposes a generalizable self-supervision method that leverages large-scale unlabeled human videos for training. Additionally, Sapiens [29] demonstrates strong performance by pretraining on large-scale human image datasets. Despite these advancements, these image-based methods often struggle with temporal consistency and fine geometric details when applied to video geometry estimation, as shown in Fig. 4.

Video Geometry Estimation. To enhance temporal consistency in video geometry estimation, one approach involves test-time optimization [11, 31, 34, 68], which refines predictions using optical flow or camera poses. While effective, this post-processing step is often computationally expensive. Meanwhile, methods [23, 57] developed for generic object video geometry estimation often yield unsatisfying

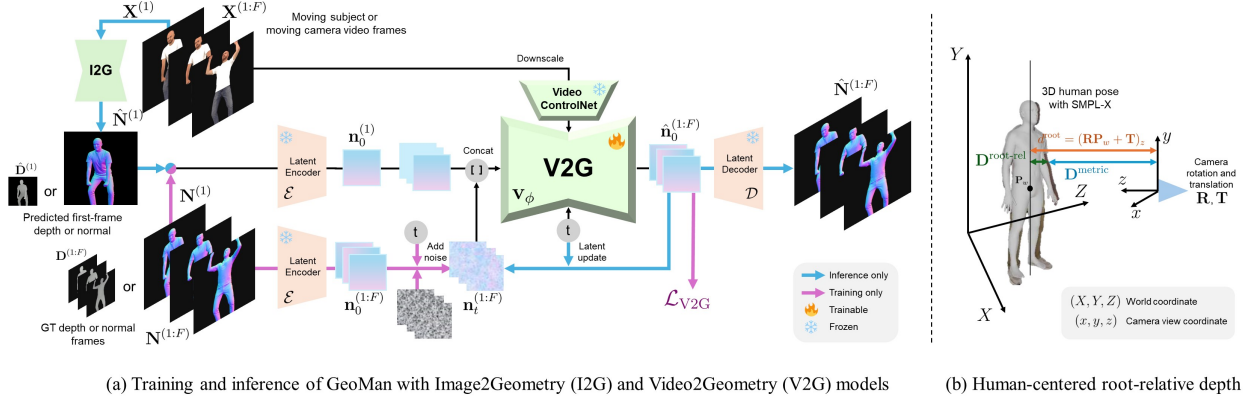


Figure 2. Overview of GeoMan: (a) Given a video sequence $\mathbf{X}^{(1:F)}$ as input, we first use I2G to estimate the normal or depth of the first frame $\mathbf{X}^{(1)}$. This initial prediction is then used to condition the V2G model, which generates predictions for the entire input sequence. GeoMan seamlessly handles both depth and normal estimation tasks using the same model weights, requiring only a replacement of the input condition for the first frame. (b) We propose a human-centered root-relative depth representation, which retains the human scale information and enables better temporal modeling.

precision when applied to human videos. In this paper, we aim at predicting both temporally stable and accurate geometry from human videos.

Depth Representations. Existing depth estimation methods primarily utilize affine-invariant or metric depth representation. Affine-invariant depth methods [14, 17, 23, 28, 57] normalize depth maps using the minimum and maximum depth values of each image, effectively capturing relative depth structures while remaining robust to scale variations. However, the lack of absolute scale information limits their applicability to tasks requiring metric measurements. Metric depth estimation methods [3, 5, 37, 60] recover depth in real-world units, enabling precise spatial reasoning. Yet, these methods often sacrifice fine geometric details due to the large numeric range of metric depth values, leading to less accurate local structure preservation. To address these limitations, we propose a root-relative depth representation that integrates human characteristics into depth representation. As shown in Fig. 3, our approach enables metric depth estimation while preserving local geometric details, which cannot be achieved simultaneously by affine-invariant or metric depth estimation methods.

Image and Video diffusion model. Diffusion models [19, 48] have emerged as powerful tools for generating high-quality images [12, 38, 39, 42, 43, 64] and videos [2, 4, 6, 8–10, 18, 49, 51, 67, 70] from text descriptions. Advancements such as Stable Video Diffusion (SVD) [4], and Video Diffusion Models (VDM) [20] generate videos with temporal consistency, while SORA [6] recently set new benchmarks in photorealism and long-duration coherence. To enhance controllability, few approaches integrate additional conditioning signals such as depth, skeletons, or optical flow [13, 21, 32, 52]. Notably, Ctrl-Adapter [32] introduces an adapter module that enables fine-grained control over image and video diffusion models by leveraging pre-

trained ControlNet [65], allowing users to specify motion trajectories, structural constraints, and content attributes. We propose a novel framework that repurposes both image and controllable video diffusion models to generate accurate, temporal and multi-view consistent human geometry.

3. Preliminaries

3.1. Geometry Estimation via Image Diffusion

Recent methods have improved monocular depth [14, 28] and normal estimation [14] by leveraging image diffusion models [41] pre-trained on large-scale datasets. The pioneering work Marigold [28] frames monocular depth estimation as a conditional image generation task, where the goal is to learn the conditional distribution $p(\mathbf{D} | \mathbf{X})$ over depth $\mathbf{D} \in \mathbb{R}^{H \times W}$, using the RGB image $\mathbf{X} \in \mathbb{R}^{3 \times H \times W}$ as the condition. To improve computational efficiency, Marigold adopts the Latent Diffusion Model (LDM) [41] architecture which leverages a latent representation learned via a Variational Autoencoder (VAE) [30]. The encoder $\mathcal{E}$ maps the depth map $\mathbf{D}$ to the latent representation: $\mathbf{d} = \mathcal{E}(\mathbf{D})$ while the decoder $\mathcal{D}$ reconstructs the depth map from the latent: $\hat{\mathbf{D}} = \mathcal{D}(\mathbf{d})$. The RGB input $\mathbf{X}$ is similarly encoded as $\mathbf{x} = \mathcal{E}(\mathbf{X})$. Next, in the forward diffusion process, Gaussian noise is added to the depth latent feature $\mathbf{d}_0 := \mathbf{d}$ over T steps: $\mathbf{d}_t = \sqrt{\bar{\alpha}_t} \mathbf{d}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$, where $\epsilon \sim \mathcal{N}(0, I)$, $\bar{\alpha}_t := \prod_{s=1}^t (1 - \beta_s)$, and $\{\beta_1, \dots, \beta_T\}$ defines the variance schedule. The model is optimized by minimizing the denoising diffusion objective:

$$\mathcal{L} = \mathbb{E}_{\mathbf{d}_0, \epsilon \sim \mathcal{N}(0, I), t \sim \mathcal{U}(T)} \|\epsilon - \epsilon_\theta(\mathbf{d}_t, \mathbf{x}, t)\|_2^2. \quad (1)$$

To ensure stable performance, the v -objective [46] is used by reparameterizing the denoiser as $\epsilon_\theta(\mathbf{d}_t, \mathbf{x}, t) = \frac{1}{\alpha_t}(\mathbf{d}_t - \sigma_t \mathbf{v}_\theta(\mathbf{d}_t, \mathbf{x}, t))$. During inference, $\mathbf{d}_0$ is obtained by starting from a Gaussian noise $\mathbf{d}_T \sim \mathcal{N}(0, I)$, and iteratively

applying the denoiser $\epsilon_\theta(\cdot)$. Finally, the decoder $\mathcal{D}$ reconstructs the depth map $\hat{\mathbf{D}}$ from the estimated clean latent $\hat{\mathbf{d}}_0$.

3.2. Controllable Video Generation Models

Using image-to-video (I2V) diffusion models [4, 67], recent video generation methods synthesize videos from a single image by modeling the conditional distribution $p(\mathbf{X}^{(1:F)} | \mathbf{X}^{(1)})$, where $\mathbf{X}^{(1)} \in \mathbb{R}^{3 \times H \times W}$ is an input image and $\mathbf{X}^{(1:F)} \in \mathbb{R}^{F \times 3 \times H \times W}$ represents the generated video frames. Controllable video generation methods [32] incorporate additional guidance (e.g., depth or normal) to enforce structural consistency. This extends the formulation to $p(\mathbf{X}^{(1:F)} | \mathbf{X}^{(1)}, \mathbf{D}^{(1:F)})$, where $\mathbf{D}^{(1:F)} \in \mathbb{R}^{F \times H \times W}$ represents depth or normal maps that provide geometric information. In this work, we formulate video depth and normal estimation as an image-to-video generation task, building our system upon both image geometry estimation models [28] and conditional video generation frameworks [32].

4. GeoMan

GeoMan aims to estimate temporally consistent and accurate depth and normal maps from monocular human videos. Our key idea is to frame video geometry estimation as an image-to-video generation task (Sec. 4.1), leveraging the pre-trained priors of image-to-video models learned with large-scale video datasets. To preserve human scale information in the estimated depth maps, we propose a novel human-centered metric depth representation in Sec. 4.2 that computes root-relative distances as the depth measurement. We explain the process of synthesizing training data to train our models using 3D and 4D human scans in Sec. 4.3.

4.1. Temporal Human Geometry Estimation

Given a monocular RGB video of a single moving human, $\mathbf{X}^{(1:F)} \in \mathbb{R}^{F \times 3 \times H \times W}$, our objective is to estimate dynamic human geometry, including depth maps $\mathbf{D}^{(1:F)} \in \mathbb{R}^{F \times 3 \times H \times W}$ and normal maps $\mathbf{N}^{(1:F)} \in \mathbb{R}^{F \times 3 \times H \times W}$ for all F frames in the video. To reduce dependency on 4D training data, we decompose this complex task into image-geometry estimation and image-to-video synthesis. We begin by training an Image-to-Geometry Estimation Model (I2G) that estimates the depth and normal map of the first frame in a video. This initial estimation serves as guidance for our Video-to-Geometry Estimation Model (V2G), which predicts the depth or normal maps for subsequent frames. As demonstrated in Tab. 5(a) and Fig. 6, our approach reduces reliance on extensive 4D training datasets, while achieving superior performance and strong generalization ability. Fig. 2(a) shows an overview of GeoMan.

Image-to-Geometry Estimation Model (I2G). We predict geometry for the first frame by modeling the conditional distributions $p(\mathbf{D}^{(1)} | \mathbf{X}^{(1)})$ and $p(\mathbf{N}^{(1)} | \mathbf{X}^{(1)})$. In-

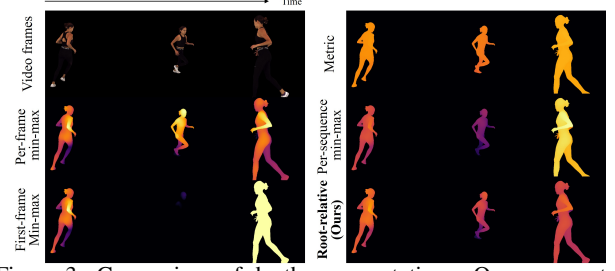


Figure 3. Comparison of depth representations: Our representation offers the highest fidelity and improves temporal modeling.

Method	Aff-invariant	Metric	Root-relative
Formulation	$\frac{D - \min(D)}{\max(D) - \min(D)}$	D	$D - d_{\text{root}}$
Range	$[0, 1]$	$[0, \infty]$	$[-h/2, h/2]$
Scale preservation	✗	✓	✓
Temporal consistency	✗	✓	✓
Detail preservation	✓	✗	✓

Table 1. Comparison of different depth representations. h is the maximum human height. We divide h by 2 because the root key-point is roughly in the middle of the body.

spired by Marigold [28], we learn a LDM [16] within the latent space of a pre-trained VAE model [30] for depth and normal estimation. More details can be found in Sec. 3.1, Sec. B.1 of the supplementary material and in [28]. Note that we learn two separate diffusion models for depth and normal prediction, which yields better performance compared to sharing a single model across two modalities.

Video-to-Geometry Estimation Model (V2G). Given the geometry estimations from the first frame as discussed above, we formulate geometry estimation for the subsequent frames as modeling the conditional distributions $p(\mathbf{D}^{(1:F)} | \mathbf{X}^{(1:F)}, \mathbf{D}^{(1)})$ and $p(\mathbf{N}^{(1:F)} | \mathbf{X}^{(1:F)}, \mathbf{N}^{(1)})$. We adopt a ControlNet-based diffusion model [32] that takes the video frames $\mathbf{X}^{(1:F)}$ as control inputs and the first frame’s geometry (depth $\mathbf{D}^{(1)}$ or normal $\mathbf{N}^{(1)}$) as a reference image. As illustrated in Fig. 2(a), we learn a unified model for both depth and normal estimation, which can be achieved by simply switching the reference image input between depth $\mathbf{D}^{(1)}$ or normal map $\mathbf{N}^{(1)}$ of the first frame. Our intuition is that by framing video geometry estimation as an image-to-video synthesis task, depth and normal maps of the first frame are solely used as a reference image while the fundamental task (i.e., image-to-video synthesis) remains the same for both modalities, hence it enables us to share a single model across two modalities. In the following, we assume the reference image is a normal map, depth estimation can be similarly performed by changing the reference image to a depth map.

At each training step, we map the normal maps to the latent space by a pre-trained encoder and add noise to the normal latents $\mathbf{n}^{(1:F)}$ at a random timestep t . We concatenate the latents of the first frame’s normal with noisy normal latents and pass them to the video denoising model to

estimate the added noise, where the input video frames are injected into the denoising model as control signal using a ControlNet. We adopt the v -objective [46] to ensure stable performance. We optimize the denoiser by minimizing the difference between the estimated and ground truth velocity:

$$\mathcal{L}_{V2G} = \mathbb{E}_{\mathbf{n}_0^{(1:F)}, \epsilon, t} \left\| \mathbf{v}_t - \mathbf{v}_\phi(\mathbf{n}_t^{(1:F)}, \mathbf{n}^{(1)}, \mathbf{X}^{(1:F)}, t) \right\|_2^2, \quad (2)$$

where $\mathbf{v}_\phi$ denotes our velocity prediction model, $\mathbf{v}_t = \alpha_t \epsilon - \sigma_t \mathbf{n}_0^{(1:F)}$, $\epsilon \sim \mathcal{N}(0, I)$, $t \sim \mathcal{U}(T)$, and $\mathbf{n}_t^{(1:F)}$ represents the noisy normal latents at timestep t . During inference, we start from a sequence of random noise maps and gradually denoise them to normal maps, using the video frames as control signals and the first frame’s normal prediction from I2G as the reference image.

Compared to existing video depth and normal estimation works [27, 29, 56], our V2G model provides two key advantages: 1) *Efficient utilization of pre-trained representations*: By leveraging a pre-trained image-to-video model, we exploit the powerful prior learned from large-scale video datasets. This enables efficient training with less data while enhancing both temporal consistency and geometric accuracy. 2) *Multi-modality compatibility*: The model utilizes shared weights across tasks, toggling between depth and normal estimation by switching the reference image. This enables simultaneous training for both modalities, improving prediction accuracy (See Table 5). As a result, our V2G model demonstrates strong generalizability, effectively handling *long video* sequences and *multi-person* scenarios. Please refer to Sec. C.1 in supplementary for details.

4.2. Human-Centered Root-Relative Depth

A major challenge in monocular depth estimation lies in selecting an optimal depth representation. Most existing methods [28, 29] employ an affine-invariant depth representation with per-frame normalization, which loses crucial information about human scale, and leads to inferior temporal stability. Recent video depth estimation methods [28, 29] introduce per-sequence normalization to improve stability across sequences, though they often struggle to capture fine details effectively. Conversely, methods [3, 5] predicting metric depth directly often sacrifice spatial details, compromising the accuracy of geometry estimation. Fig. 3 provides an intuitive comparison of different depth representations.

To address these limitations, we propose a human-centered root-relative depth representation that preserves metric-scale details while only discarding global translation. This representation ensures accurate human size and scale, which is crucial for tasks requiring precise human geometry (e.g., human reconstruction). As shown in Fig. 2(b), the root-relative depth of each pixel is computed as the distance between the human root (i.e., the pelvis joint) and each point on the human surface. Formally, the root-relative depth $\mathbf{D}^{\text{root-rel}}$ is computed as $\mathbf{D}^{\text{root-rel}} = \mathbf{D}^{\text{metric}} - d^{\text{root}}$,

where $\mathbf{D}^{\text{metric}}$ is the metric depth, d^{root} is the depth of the root joint, which can be obtained via pose estimation techniques [15, 54]. For training, we obtain the root joint’s depth using the SMPL-X [36] annotation in the datasets. Given the SMPL-X pelvis joint location in world space $\mathbf{P}_w \in \mathbb{R}^3$, the camera rotation matrix $\mathbf{R} \in \mathbb{R}^{3 \times 3}$ and translation vector $\mathbf{T} \in \mathbb{R}^3$, we compute the root depth as $d^{\text{root}} = (\mathbf{R}\mathbf{P}_w + \mathbf{T})_z$, as illustrated in Fig. 2(b).

We compare depth representations in Table 1. Root-relative depth offers several key advantages: 1) *Human scale preservation*: It retains the relative depth information of the person in metric scale, allowing inference of real human size. In contrast, affine-invariant depth always normalizes this size to 1, discarding meaningful scale information. Additionally, absolute metric depth can be easily predicted by combining root-relative depth with root depth estimated by advanced human pose prediction models [15, 54]. 2) *Temporal consistency*: Root-relative depth is more temporally stable, as it avoids per-frame normalization using varying $\min(D)$ and $\max(D)$, which is required for affine-invariant depth and can introduce temporal artifacts. 3) *Geometric detail preservation*: The range of root-relative depth is constrained to $[-h/2, h/2]$, determined by the maximum human height (h) and independent of global position. In contrast, metric depth spans a much wider range (e.g., $[0, \infty]$), making it harder for networks to focus on fine-grained geometry.

4.3. Training with Limited Geometric Video Data

We synthesize our training data by rendering 3D scans from the THuman-2.0 [61] dataset and 4D scans from the XHumans [47, 50] dataset using diverse camera distance, pitch angles, and focal lengths. To train the I2G model, we rendered 40K frames from the THuman-2.0 [61] dataset, which consists of 525 high-resolution, textured 3D scans with approximately 300K vertices per scan. For training the V2G model, we addressed the limited diversity in sequences and subjects by combining data from the XHumans [47] dataset (233 sequences across 20 subjects) with augmented data derived from THuman-2.0.

In total, our model is trained using only 20 subjects in 4D [47] and around 500 subjects in 3D [61] from public datasets. While this dataset is significantly smaller compared to the large-scale proprietary datasets employed by state-of-the-art methods [27, 29], our approach demonstrates strong performance.

5. Experiments

The supplementary material includes experimental details, additional results on the Goliath dataset [35], in-the-wild videos, long videos, and multi-person scenarios.

Evaluation Dataset. We use ActorsHQ [25] as our primary evaluation dataset for its high-quality dynamic geometry (~30K vertices) and independence from training sets. For

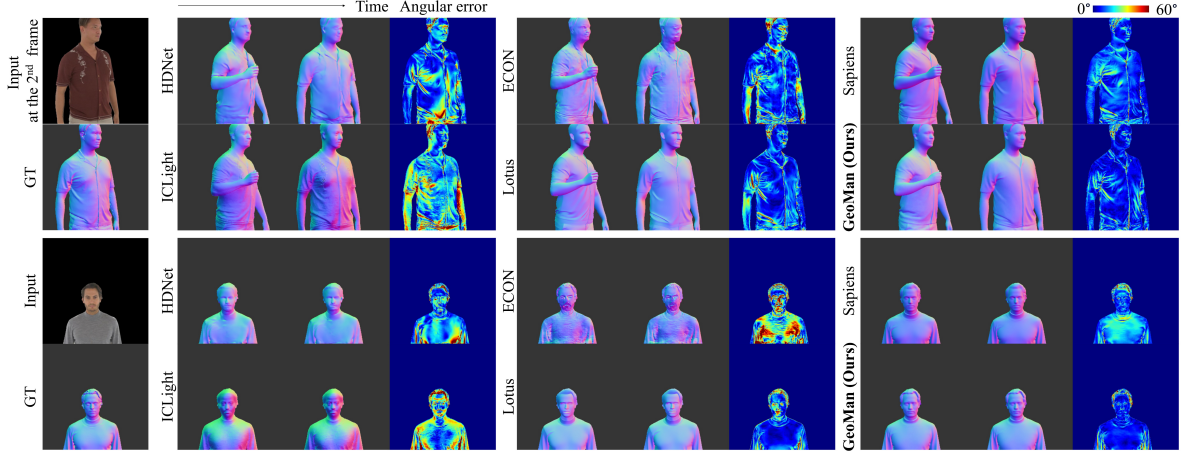


Figure 4. Zero-shot normal estimation comparison on ActorsHQ. **Left:** Predicted normal for the first frame. **Middle:** Predicted normal for the second frame. **Right:** Angular error visualization for the second frame.

	Performance on moving subject videos				Performance on moving camera videos				Temporal consistency		
	Mean↓	Median↓	11.25°↑	30°↑	Mean↓	Median↓	11.25°↑	30°↑	OPW↓	TC-Mean↓	TC-11.25°↑
ECON [56]	29.228	23.766	17.963	62.464	27.202	22.089	19.652	66.682	0.173	16.371	50.469
ICLight [66]	27.996	23.555	16.384	64.276	26.975	22.529	17.595	66.567	0.122	11.476	66.866
HDNet [27]	24.477	20.329	21.737	71.527	23.954	19.867	22.493	72.764	0.134	12.398	62.957
GeoWizard [14]	22.714	19.151	23.446	75.610	22.054	18.520	24.796	76.981	0.178	16.584	43.846
Lotus [17]	18.780	14.937	34.947	83.743	18.101	14.444	36.605	85.217	0.079	8.782	79.397
Sapiens* [29]	18.338	14.526	36.498	85.009	18.048	14.425	36.706	85.760	0.094	9.494	77.567
Sapiens [29]	16.278	13.015	41.245	89.177	16.099	12.941	41.539	89.617	0.082	7.861	82.803
GeoMan (Ours)	16.185	12.334	45.217	87.784	15.535	11.657	48.168	88.789	0.070	6.876	96.757

Table 2. Comparison on zero-shot normal estimation on ActorsHQ dataset. Sapiens*: fine-tuned on our dataset. GeoMan outperforms state-of-the-art methods despite using only public data, unlike Sapiens which was trained using large-scale proprietary data. The drop in performance of Sapiens when fine-tuned on our dataset highlights the importance of its proprietary data in its performance.

evaluation, we generate 192 videos of moving subjects with static cameras and 256 videos with moving cameras and static subjects. The full evaluation dataset includes more than 10K frames rendered at 512×512 resolution. Additional results on the Tiktok [26] and the Goliath [35] dataset can be found in Sec. C.2 and Sec. C.3 of the supplementary.

5.1. Surface Normal Estimation

Baselines. We compare our method against baselines including HDNet [26, 27], ECON [56], and Sapiens [29], which are state-of-the-art normal estimation models trained on human-centric data. Notably, methods like Sapiens and HDNet were trained using proprietary human-centric datasets, whereas our model was trained on publicly available datasets. Additionally, we compare against models trained for generic scenes, such as GeoWizard [14], Lotus [17], and ICLight [66]. For all comparisons, we used the official checkpoints provided by the authors. Additionally, we report the performance of Sapiens, the best-performing baseline, fine-tuned on our dataset.

Metrics. We report mean and median angular error, along with the percentage of pixels within t° error for $t \in \{11.25^\circ, 30^\circ\}$. To assess temporal consistency, we provide the optical flow-based warping metric (OPW) [7], as well as the optical flow-based angular error (TC-Mean) and the

11.25° metric (TC-11.25°).

Results. As shown in Table 2, GeoMan outperforms previous approaches, achieving higher accuracy in normal prediction and better temporal consistency. While GeoMan significantly outperforms other methods, Sapiens [29] performs competitively. However, it is important to note that Sapiens was trained on a proprietary dataset. For a fair comparison, we also fine-tune Sapiens’s pre-trained MAE model on our dataset. As we can see, under this more fair setting, GeoMan outperforms Sapiens by a notable margin. Fig. 4 demonstrates that GeoMan delivers more consistent estimations over time and higher fidelity.

5.2. Depth Estimation

Baselines. For metric depth estimation, we compare with state-of-the-art methods including Metric3Dv2 [22], UniDepth [37], ZoeDepth [3], and Depth Pro [5]. For affine-invariant depth estimation, we benchmark against image-based models such as Sapiens [29], Marigold [28], GeoWizard [14], and Lotus [17]. Additionally, we include video-based methods like DepthCrafter [23] and Depth Any Video [57], which are trained on large-scale video datasets. For all baselines, we used official checkpoints.

Metrics. For metric depth estimation, we follow existing methods [5] and report δ_1 and SI-log10 (Scale-Invariant

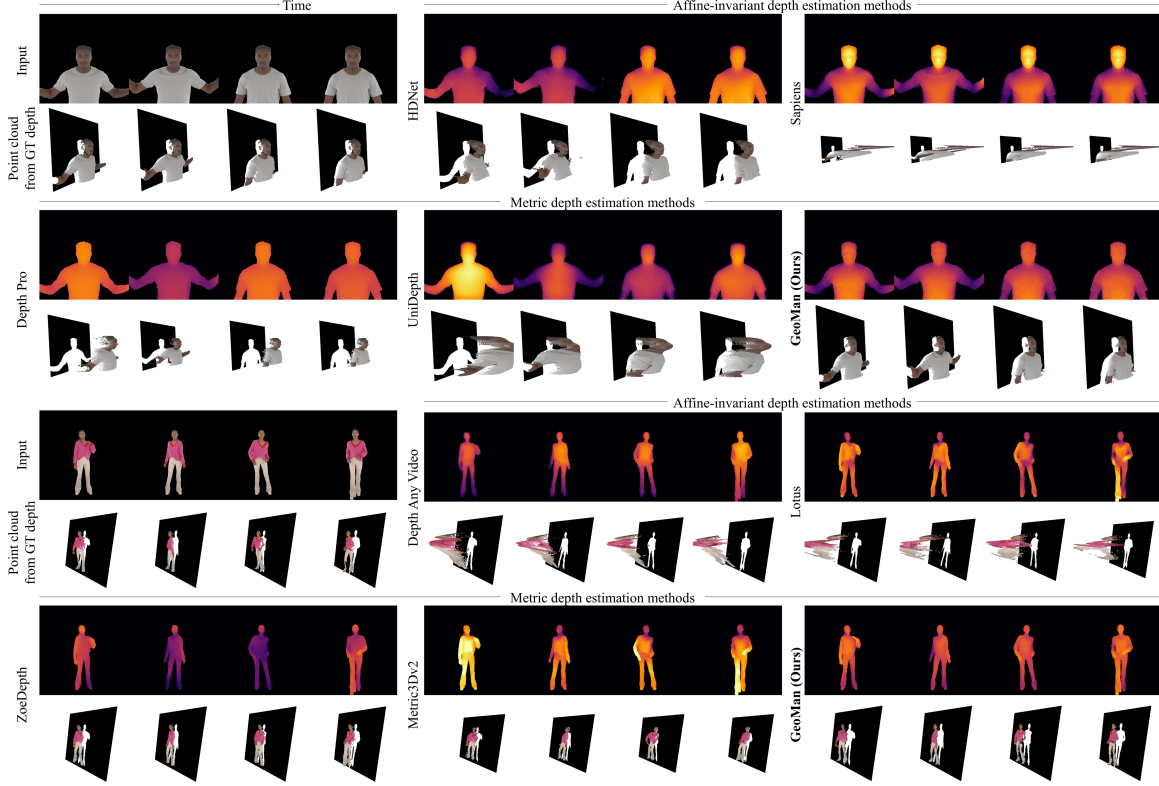


Figure 5. Comparison with existing depth estimation models. GeoMan achieves state-of-the-art performance in both depth prediction (top row in each result) and point cloud reconstruction (bottom row), excelling in temporal consistency, fidelity, and scale preservation.

	Performance on moving subject videos				Performance on moving camera videos				Temporal consistency		
	Absolute		Optimizing scale + shift		Absolute		Optimizing scale + shift		OPW↓	TC-RMSE↓	TC- δ_1 ↑
	δ_1 ↑	SI-log10↓	AbsRel↓	$\delta < 1.05$ ↑	δ_1 ↑	SI-log10↓	AbsRel↓	$\delta < 1.05$ ↑			
ZoeDepth [3]	0.016	2.710	0.016	0.960	0.000	2.487	0.018	0.955	0.058	0.017	0.830
UniDepth [37]	0.058	8.027	0.025	0.883	0.003	7.790	0.022	0.915	0.128	0.031	0.564
Depth pro [5]	0.127	5.297	0.026	0.865	0.103	5.804	0.025	0.882	0.201	0.046	0.388
Metric3Dv2 [22]	0.491	6.213	0.016	0.958	0.697	5.804	0.019	0.944	0.085	0.023	0.743
GeoMan (Ours)	0.972	2.116	0.011	0.984	0.987	1.775	0.009	0.992	0.038	0.015	0.898
GeoMan w GT root-depth (Ours)	0.998	2.118	0.011	0.984	0.998	1.775	0.009	0.992	0.032	0.015	0.915

Table 3. Comparison with metric depth estimation methods on zero-shot settings on ActorsHQ dataset.

	Performance on moving subject videos				Performance on moving camera videos				Temporal consistency		
	Optimizing shift		Optimizing scale + shift		Optimizing shift		Optimizing scale + shift		OPW↓	TC-RMSE↓	TC- δ_1 ↑
	AbsRel↓	$\delta < 1.05$ ↑	AbsRel↓	$\delta < 1.05$ ↑	AbsRel↓	$\delta < 1.05$ ↑	AbsRel↓	$\delta < 1.05$ ↑			
HDNet [27]	0.031	0.808	0.024	0.877	0.030	0.821	0.021	0.921	0.108	0.027	0.604
Sapiens [29]	0.040	0.680	0.009	0.986	0.041	0.663	0.010	0.987	0.058	0.018	0.792
Sapiens* [29]	0.021	0.915	0.015	0.959	0.017	0.960	<u>0.013</u>	<u>0.980</u>	0.054	0.018	0.816
Marigold [28]	0.021	0.901	0.021	0.901	0.015	0.956	0.017	0.951	0.074	0.027	0.547
GeoWizard [14]	0.018	0.935	0.019	0.930	0.014	0.967	0.017	0.952	0.053	0.023	0.667
Lotus [17]	0.022	0.899	0.019	0.919	0.016	0.954	0.015	0.962	0.077	0.025	0.637
DepthCrafter [23]	0.016	0.944	0.013	0.967	0.012	0.976	0.018	0.945	0.037	0.016	0.914
Depth-Any-Video [57]	0.018	0.928	0.015	0.955	0.014	0.971	0.018	0.948	0.039	0.017	0.823
GeoMan (Ours)	0.012	0.978	<u>0.011</u>	<u>0.984</u>	0.009	0.991	0.009	0.992	0.032	0.014	0.915

Table 4. Comparison with affine-invariant depth estimation methods in zero-shot on ActorsHQ. Sapiens*: fine-tuned on our dataset.

Logarithmic Error). The root depth is obtained using 3D pose estimation method [54] to convert our predictions to metric depth. For evaluating affine-invariant depth estimation methods, we align the predicted depth maps with the ground truth using two approaches: (1) optimizing only the shift to highlight the benefits of GeoMan’s learned human scale, and (2) optimizing both scale and shift before

computing the metrics. We report AbsRel (absolute relative error) and $\delta < 1.05$ (the percentage of pixels where $\max(d/\hat{d}, \hat{d}/d) < 1.05$). We further report affine-invariant metrics for metric depth estimation methods to provide a comprehensive assessment. To evaluate temporal consistency, we report the optical flow-based warping metric (OPW) [53], RMSE, and the δ_1 metric. Details of all met-

	Normal					Depth					
	Angular difference		%within 1°	Temporal consistency		Optimizing shift		Optimizing scale + shift		Temporal consistency	
	Mean↓	Median↓	11.25°↑	OPW↓	TC-Mean↓	AbsRel↓	$\delta < 1.05^\circ$ ↑	AbsRel↓	$\delta < 1.05^\circ$ ↑	OPW↓	TC-RMSE↓
(a) Naïve extension vs GeoMan across training steps											
Naïve-5K-steps	25.305	22.732	15.602	0.076	7.458	0.038	0.720	0.028	0.856	0.049	0.019
Naïve-30K steps	19.669	16.628	28.405	0.072	7.169	0.020	0.926	0.017	0.943	0.040	0.016
GeoMan-5K steps	17.499	13.541	40.340	0.069	6.781	0.014	0.964	0.013	0.970	0.036	0.014
GeoMan-30K steps	16.185	12.334	45.217	0.070	6.876	0.012	0.978	0.011	0.984	0.032	0.014
(b) Naïve extension vs GeoMan on 1/10 training data (at 30K steps)											
Naïve w/ 1/10 data	22.329	19.626	20.568	0.068	6.833	N/A	N/A	N/A	N/A	N/A	N/A
GeoMan w/ 1/10 data	17.679	13.559	40.263	0.065	6.451	0.013	0.975	0.011	0.982	0.032	0.014
(c) Multimodality of V2G											
Unimodal	16.260	12.361	45.091	0.073	7.190	0.012	0.976	0.011	0.983	0.038	0.015
Multimodal	16.185	12.334	45.217	0.070	6.876	0.012	0.978	0.011	0.984	0.032	0.014
(d) Source of the first frame for V2G											
GT+V2G	14.028	10.101	54.924	0.078	7.536	0.009	0.985	0.009	0.988	0.032	0.014
I2G+V2G	16.185	12.334	45.217	0.070	6.876	0.012	0.978	0.011	0.984	0.032	0.014

Table 5. Ablation studies. We validate the impact of various design choices.

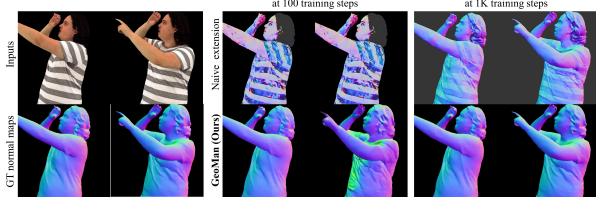


Figure 6. Comparison of naive extension and GeoMan across training steps. Results here are evaluated on the validation data.

rics can be found in Sec. B.3 in the supplementary.

Results. Table 3 shows GeoMan significantly outperforms other metric depth estimation methods, beating Metric3Dv2 by $\sim 100\%$ in δ_1 and $\sim 65\%$ in SI-log10. While ZoeDepth has better temporal consistency, its accuracy is much lower due to overly smooth predictions (Fig. 5). Using ground-truth root depth from the pose estimation method VIMO [54] further improves results, indicating future enhancement potential. Table 4 compares GeoMan with affine-invariant depth methods. Our model excels when optimizing only the shift, showing the advantage of our root-relative depth in capturing human-scale information. We also outperform most baselines with both scale and shift optimization with superior temporal consistency.

Fig. 5 qualitatively compares our approach with baselines. All depth maps are renormalized using sequence-wise min-max scaling within the human mask, per [29]. Our method produces more temporally stable results than per-frame estimation models. While UniDepth [37] and DepthCrafter [23] improve temporal consistency, our model achieves higher visual and quantitative accuracy. The second row of Fig. 5 compares point cloud reconstructions (PCDs). Prior methods yield distorted and temporally inconsistent reconstructions, whereas GeoMan ensures accurate scaling and superior temporal consistency.

5.3. Ablation Studies and Analysis

Naïve Extension vs. GeoMan. We compare our approach with a naïve extension of [23, 28]. Unlike GeoMan’s I2G and V2G decomposition, this extension trains a video diffusion model to predict normal or depth maps for all frames in

a single pass, without a control module. This design suffers from a task gap, failing to effectively utilize prior knowledge and resulting in suboptimal performance. Table 5(a) shows GeoMan’s superior performance even at early (5K) iterations, outperforming the naïve extension at 30K iterations. This gap stems from the direct prediction of geometric information for all frames, which significantly deviates from the video diffusion model’s original task. Consequently, the naïve extension poorly leverages its prior, as seen in Fig. 6. GeoMan’s superior generalization is further demonstrated by training both models on a reduced dataset (1/10 original). The naïve extension suffers significantly, showing poor normal model performance and depth model explosion, as presented in Table 5(b).

Multimodality of V2G. Another advantage of GeoMan’s image-to-video formulation is its ability to share model weights between the normal and depth prediction by simply switching the reference image. This enables training on multi-modal data, improving both generalization and training efficiency. Table 5(c) shows that the multi-modal model achieves superior results compared to task specific models, demonstrating the effectiveness of our formulation.

Source of the First Frame for V2G. Tab. 5(d) shows that replacing I2G predictions with ground-truth normal or depth improves V2G’s performance, highlighting the potential for further gains by refining the image-based I2G model.

6. Conclusion

We introduce GeoMan, a novel framework for accurate and temporally consistent depth and normal estimation from monocular videos. GeoMan addresses the challenge of 4D human data scarcity by framing the video geometry estimation task as image-to-video synthesis. To preserve human scale information, we proposed a root-relative depth representation tailored for human geometry. Extensive experiments on high-resolution benchmarks showed that GeoMan surpasses existing methods, even those trained on large-scale proprietary data, demonstrating effectiveness in real-world video geometry estimation and 3D reconstruction.

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