

Geo4D: Leveraging Video Generators for Geometric 4D Scene Reconstruction

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geo4d.github.io

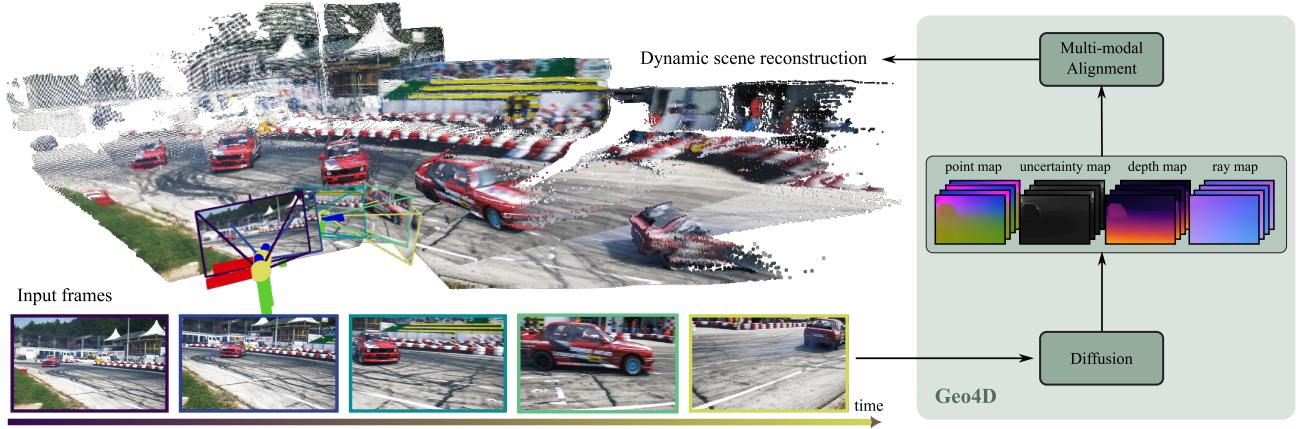


Figure 1. Geo4D repurposes a video diffusion model [102] for monocular 4D reconstruction. It uses only synthetic data for training, but generalizes well to real data. It predicts several geometric modalities, including point maps, depth maps, and ray maps, fusing and aligning them to obtain state-of-the-art dynamic reconstruction even for scene with extreme object and camera motion.

Abstract

We introduce *Geo4D*, a method to repurpose video diffusion models for monocular 3D reconstruction of dynamic scenes. By leveraging the strong dynamic prior captured by such video models, *Geo4D* can be trained using only synthetic data while generalizing well to real data in a zero-shot manner. *Geo4D* predicts several complementary geometric modalities, namely point, depth, and ray maps. We introduce a new multi-modal alignment algorithm to align and fuse these modalities, as well as multiple sliding windows, at inference time, thus obtaining robust and accurate 4D reconstruction of long videos. Extensive experiments across multiple benchmarks show that *Geo4D* significantly surpasses state-of-the-art video depth estimation methods, including recent methods such as *MonST3R*, which are also designed to handle dynamic scenes.

1. Introduction

We consider the problem of *feed-forward 4D reconstruction*, which involves learning a neural network to recon-

struct the 3D geometry of a dynamic scene from a monocular video. This task is particularly challenging for videos captured in uncontrolled settings, such as those shot with handheld cameras or downloaded from the Internet. However, a robust solution to this problem would have a tremendous impact on a wide range of applications, from video understanding to computer graphics and robotics.

4D reconstruction from videos is related to multi-view static 3D reconstruction, which is typically addressed using methods from visual geometry like bundle adjustment. New neural networks [89, 92] have recently emerged as powerful tools that can replace, or at least complement, bundle adjustment. They excel especially in difficult reconstruction scenarios, involving, e.g., textureless surfaces and occlusions, thanks to the priors that they learn from data. Because of the additional challenges involved in 4D reconstruction, we expect that such priors would benefit this task even more.

In fact, powerful networks like DUS3R [92], designed for static multi-view 3D reconstructions, have recently been extended to the dynamic case, for example by *MonST3R* [113]. However, these models are heavily engineered to solve specific 3D reconstruction problems. Most importantly, they require significant amounts of train-

ing data with 3D annotations for supervision. Such data is difficult to collect for dynamic scenes, especially in real life. This suggests using 4D synthetic training data instead. However, this data is difficult to obtain at scale, and the gap with the real world can compromise generalization.

One way to mitigate this problem is to pre-train the model on tasks related to 3D reconstruction for which real data is easily available. For example, DUST3R and derived methods use image matching for pre-training [98]. Here, we suggest starting instead from an off-the-shelf *video generator*. Video generators are powerful models, often considered proxies of world simulators [37, 54, 59]. More importantly for us, the videos that they generate show an understanding of effects like camera motion and perspective as well as typical object motion in the context of that scene. However, they only generate pixels, leaving any 3D or 4D understanding *implicit* and thus not directly actionable.

In this work, we show that *a pre-trained off-the-shelf video generator* can be turned into an effective *monocular feed-forward 4D reconstructor*. To this end, we introduce **Geo4D**, a novel approach for adapting Video Generators for **Geometric 4D Reconstruction**. With Geo4D, we demonstrate that these generic video architectures can successfully solve complex 4D reconstruction tasks, which is a step towards future video foundation models that natively integrate 4D geometry. Prior works like Marigold [28] and concurrent work DepthCrafter [22] have looked at adapting, respectively, image and video generators for depth estimation. Here, we go one step further and consider *the full recovery of 4D geometry, including camera motion and dynamic 3D structure*.

With Geo4D, our goal is to make 4D geometry explicit in the video generator. This in turn requires us to choose an *explicit representation* of 4D information. We follow DUST3R and adopt its viewpoint-invariant point maps. Namely, we associate each pixel in each frame with the coordinate of the corresponding 3D point, expressed relative to the first frame in the video, used as a reference. Hence, the static parts of the point clouds extracted from the different frames line up, and the dynamic parts form a 3D ‘trace’ of the motion of the dynamic objects, as shown in Fig. 1.

Viewpoint-invariant point maps are a powerful representation because they implicitly encode the camera motion and intrinsics, and because they can be easily predicted by a neural network [92]. However, they are not necessarily the best representation for all parts of the scene, particularly for points far away from the observer or even at infinity, such as the sky. We thus consider two more *modalities*, namely disparity maps and camera ray maps, with better dynamic range. Ray maps, in particular, are defined for all image pixels regardless of the scene geometry.

Our model thus predicts three modalities: point, disparity, and ray maps. These modalities are redundant in principle, but complementary in practice. At test time, we reconcile them via a fast, global optimization step and show that this leads to significantly more robust 4D reconstructions. Due to depth and ray map prediction, we show in particular very strong empirical results on video depth estimation and in the recovery of the camera orientation.

One reason why monocular 4D reconstruction is difficult is that it is ambiguous, much more so than static 3D reconstruction. The stochastic nature of the video generator can help us deal with this ambiguity. We also introduce uncertainty maps in the encoder-decoder architecture that processes the geometric maps and that are integrated into the multi-modal alignment process.

Overall, our contributions are as follows. (i) We introduce Geo4D, a 4D feed-forward network for dynamic scene reconstruction that builds on top of an off-the-shelf video generator. (ii) We suggest generating multiple partially-redundant geometric modalities and fusing them at test time via light-weight optimization. (iii) We show the benefits of this multi-modal fusion in terms of improved 4D prediction accuracy. Our experiments show that this model is able to reconstruct even highly dynamic scenes (such as the drifting scene in DAVIS [23] presented in Fig. 1) and outperforms current video depth and camera rotation estimation.

2. Related Work

2.1. Dynamic Scene Reconstruction

Static 3D Reconstruction. Feed-forward 3D reconstruction has achieved remarkable success across various representations, including voxels [11, 74, 83], meshes [18, 72, 90], and point clouds [41, 110]. These advancements have been further propelled by implicit neural representations [52, 56, 60, 75] and the emergence of 3D Gaussian Splatting [7, 9, 29, 76, 79, 80]. Recently, DUST3R [92] introduced a point map representation for scene-level 3D reconstruction, followed by [35, 86, 89, 104]. However, these models predominantly focus on *static* 3D reconstruction. Our approach also uses point maps as a representation but extends it to handle *dynamic* scenes, which presents more challenges, where objects undergo motion over time.

Iterative 4D Reconstruction. Iterative or optimization-based approaches reconstruct 4D models from monocular videos by iteratively fitting the observed data. Classical techniques often rely on RGB-D sensors [24, 53], but such steps are impractical for many real-world scenes. Recently, with advancements in neural representations [52, 56], NeRF-based approaches [27, 38, 39, 57, 58, 62] have shown impressive results. However, volume rendering in NeRF is computationally expensive. Convergence and rendering speed can be improved by using 3D Gaussian Splatting (3D-GS) representations [12, 29, 34, 43, 91, 99, 107, 111], which reduce but do not eliminate the cost of iteration.

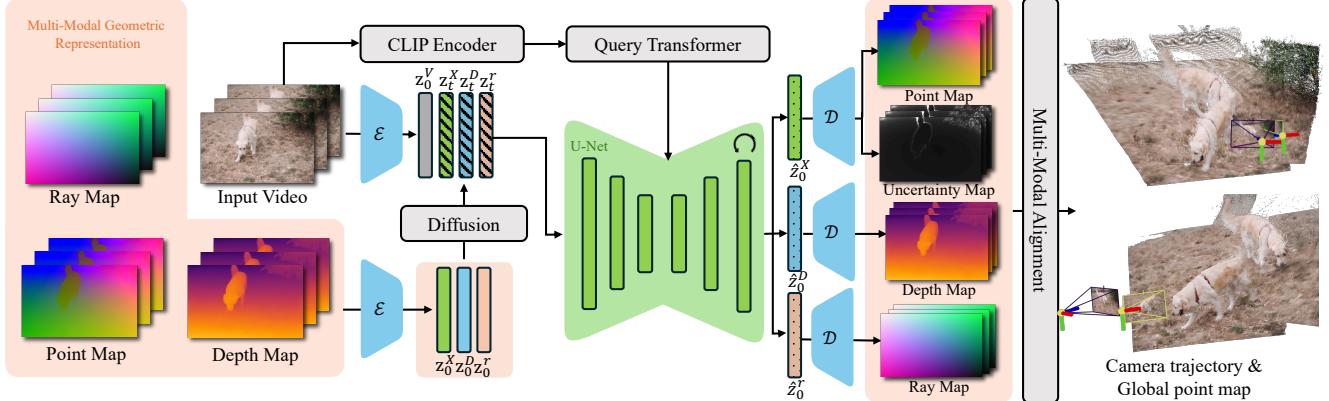


Figure 2. Overview of Geo4D. During training, video conditions are injected by locally concatenating the latent feature of the video with diffused geometric features z_t^X, z_t^D, z_t^r and are injected globally via cross-attention in the denoising U-Net, after CLIP encoding and a query transformer. The U-Net is fine-tuned via Eq. 2. During inference, iteratively denoised latent features $\hat{z}_0^X, \hat{z}_0^D, \hat{z}_0^r$ are decoded by the fine-tuned VAE decoder, followed by multi-modal alignment optimization for coherent 4D reconstruction.

tive optimization. Very recently, MegaSaM [40] achieved highly accurate and robust camera pose estimation and reconstruction for dynamic videos, but it requires accurate monocular depth prior. Similarly, Uni4D [108] produces accurate 4D reconstruction by leveraging various visual foundation models and performing multi-stage bundle adjustment. In contrast, our approach is a diffusion-driven feed-forward framework, which eliminates the need for per-video bundle adjustment and other depth estimation models.

Feed-forward 4D Reconstruction. Similar to our approach, recent works have started to explore *feed-forward* 4D reconstruction for dynamic scenes: a monocular video with dynamic objects is processed by a neural network to recover a 4D representation. For objects, L4GM [66] and Animate3D [26] first generate multi-view videos from a monocular video input, and subsequently apply 3D-GS [29] to reconstruct a temporally consistent 4D model. For scenes, a notable example is MonST3R [113], which adapts the *static* scene reconstruction of DUS3R [92] to handle *dynamic* scenes. Very recently, Easi3R [8] applies attention adaptation during inference and performs 4D reconstruction based on DUS3R [92] in an efficient training-free manner.

2.2. Geometric Diffusion Model

Our method builds upon advancements in video diffusion models [3, 4, 16, 19, 21, 31, 73, 88, 94, 102, 112], which generate *temporally consistent* videos from text or image prompts. Recent studies have explored the rich 3D priors embedded within large-scale pre-trained diffusion models, employing either knowledge distillation [25, 42, 51, 61, 87, 96] or fine-tuning [20, 36, 45–47, 71, 85, 118] for 3D reconstruction and generation. While these methods have significantly advanced single-object 3D reconstruction from sparse inputs, they remain largely constrained to *static, isolated* objects centered within an image. Beyond single-

object reconstruction, several recent efforts have extended pre-trained diffusion models to tackle scene-level 3D tasks, such as optical flow estimation [69], view synthesis [10, 15, 44, 68, 81, 109], depth estimation [13, 28, 117], and normal estimation [14, 33, 63]. More related to our approach, Matrix3D [49] jointly predicts the depth and camera parameters, and WVD [115] introduces a hybrid RGB+point maps representation for scene reconstruction. However, these approaches assume *static* 3D environments, whereas we address *dynamic* 4D scene reconstruction, which is a much harder problem due to object motion across time.

More related to our approach, concurrent GeometryCrafter [103] introduced a point map VAE with a dual encoder-decoder architecture to improve reconstruction accuracy. However, their point maps are defined in individual camera coordinates, necessitating the use of additional segmentation [30] and tracking models [101] to recover the global point map and estimate camera poses. Aether [82], on the other hand, outputs depth maps and ray maps from a video diffusion model for 4D reconstruction. In contrast, our experiments demonstrate that performance can be significantly enhanced by jointly predicting multiple geometric modalities that capture diverse dynamic ranges, ensuring better temporal coherence and robustness. Importantly, our approach is self-contained and does *not* rely on external models, enhancing its generality and reliability.

3. Method

Our goal is to learn a neural network f_θ that can reconstruct dynamic 3D scenes from monocular videos. Given as input a monocular video $\mathcal{I} = \{\mathbf{I}^i\}_{i=1}^N$ consisting of N frames, where each frame is an RGB image $\mathbf{I}^i \in \mathbb{R}^{H \times W \times 3}$, the network f_θ returns a representation of its 4D geometry:

$$f_\theta : \{\mathbf{I}^i\}_{i=1}^N \mapsto \{(\mathbf{D}^i, \mathbf{X}^i, \mathbf{r}^i)\}_{i=1}^N. \quad (1)$$

The network computes the disparity map $\mathbf{D}^i \in \mathbb{R}^{H \times W \times 1}$, the viewpoint-invariant point map $\mathbf{X}^i \in \mathbb{R}^{H \times W \times 3}$, and the ray map $\mathbf{r}^i \in \mathbb{R}^{H \times W \times 6}$ of each frame \mathbf{I}^i , $i \in 1, \dots, N$. As we discuss in Sec. 3.2, these quantities collectively represent the 4D geometry of a scene, including its dynamic structure and time-varying camera extrinsic and intrinsic parameters. No camera parameters are provided as input, so these are implicitly estimated by the model too.

We implement f_θ as a video diffusion model, where θ are the learnable parameters of the model. We discuss the relevant background on video diffusion models in Sec. 3.1. Then, in Sec. 3.2, we describe how we extend the model to predict the three modalities of the 4D geometry. Finally, in Sec. 3.3, we describe how we fuse and align these modalities to obtain a coherent 4D reconstruction at test time.

3.1. Preliminaries: Video Diffusion Model

Our key insight is that by building on pre-trained video diffusion models, our approach can exploit the strong motion and scene geometry priors inherently encoded within these models. Specifically, we build Geo4D on top of the DynamiCrafter [102], a “foundation” video diffusion model. DynamiCrafter is a latent diffusion model [67]: it uses a variational autoencoder (VAE) to obtain a smaller video representation and thus reduce the computational complexity. During training, a target sequence $\mathcal{X} = \mathbf{x}^{1:N}$, is first encoded into the latent space using the encoder $\mathbf{z}_0^{1:N} = \mathcal{E}(\mathbf{x}^{1:N})$, and then perturbed by $\mathbf{z}_t^{1:N} = \sqrt{\alpha_t} \mathbf{z}_0^{1:N} + \sqrt{1 - \alpha_t} \epsilon^{1:N}$, where $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ is the Gaussian noise, and α_t is the noise level at step t of T noising steps. The denoising network ϵ_θ is then trained to reverse this noising process by optimizing the following objective:

$$\min_{\theta} \mathbb{E}_{(\mathbf{x}^{1:N}, y), t, \epsilon^{1:N} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})} \|\epsilon^{1:N} - \epsilon_\theta(\mathbf{z}_t^{1:N}, t, y)\|_2^2, \quad (2)$$

where y is the conditional input. Once trained, the model generates a video prompted by y via iteratively denoising from pure noise $\mathbf{z}_T^{1:N}$, and then decoding the denoised latent with a decoder $\hat{\mathcal{X}} = \mathcal{D}(\hat{\mathbf{z}}_0^{1:N})$.

3.2. Multi-modal Geometric 4D Diffusion

We first provide a more precise description of the 4D multi-modal representation output by our model, and then explain how the latter is encoded in the latent space for generation.

Multi-modal geometric representations. The dynamic 3D structure of a scene is represented by a sequence of point maps $\{\mathbf{X}^i\}_{i=1}^N$, one for each of its N frames. Let (u, v) denote the pixel coordinates in the image plane. Then, the value $X_{uv}^i \in \mathbb{R}^3$ is the 3D coordinate of the scene point that lands at pixel (u, v) in frame \mathbf{I}^i , expressed in the reference frame of camera $i = 1$. Because the reference frame is fixed and independent of the time-varying viewpoint, we call these point maps *viewpoint invariant*. The

advantages of this representation are convincingly demonstrated by DUST3R [92]. For a static scene, or by knowing which image pixels correspond to the static part of a scene, knowledge of the point maps allows recovery of the intrinsic and extrinsic camera parameters as well as the scene depth. This is done by solving an optimization problem that aligns the dynamic point maps with a pinhole camera model.

As noted in Sec. 1, while point maps $\{\mathbf{X}^i\}_{i=1}^N$ fully encode the 4D geometry of the scene, they may not be as effective for all parts of the scene. Their dynamic range is limited, and in fact point maps are not even defined for points at infinity (sky). Hence, consider two more modalities, namely disparity maps $\{\mathbf{D}^i\}_{i=1}^N$ and camera ray maps $\{\mathbf{r}^i\}_{i=1}^N$, also encouraged by prior evidence [14, 33, 49] that diffusion model can benefit from learning to predict multiple quantities. Disparity maps are not viewpoint-invariant, but have better dynamic range than point maps (the disparity is zero for points at infinity). Ray maps only represent the camera parameters and are defined for all image pixels, independent of the scene geometry. For the disparity map, the value D_{uv}^i is the disparity (inverse depth) of the scene point that lands at pixel (u, v) , as seen in frame \mathbf{I}^i . For the ray map, we adopt the Plücker coordinates [75, 97, 118], i.e., $\mathbf{r}_{uv} = (\mathbf{d}_{uv}, \mathbf{m}_{uv})$, where $\mathbf{d}_{uv} = \mathbf{R}^\top \mathbf{K}^{-1}(u, v, 1)^\top$ is the ray direction and $\mathbf{m}_{uv} = -\mathbf{R}^\top \mathbf{t} \times \mathbf{d}_{uv}$, where $(\mathbf{R}, \mathbf{K}, \mathbf{t})$ are the camera’s rotation, calibration, and translation parameters.

Multi-modal latent encoding. The three modalities come in the form of images and can thus be naturally predicted by the video diffusion architecture. However, this requires first mapping them to the latent space, for which we need suitable versions of the encoder \mathcal{E} and decoder \mathcal{D} from Sec. 3.1. Related prior works [14, 28] for depth prediction simply repurposed a pre-trained image encoder-decoder without change. We found this to work well for depth and ray maps, but not for point maps. Hence, for the point maps only, we fine-tune the pre-trained decoder \mathcal{D} using the following objective function [100]:

$$\mathcal{L} = - \sum_{uv} \ln \frac{1}{\sqrt{2}\sigma_{uv}} \exp - \frac{\sqrt{2}\ell_1(\mathcal{D}(\mathcal{E}(\mathbf{X})), \mathbf{X}_{uv})}{\sigma_{uv}}, \quad (3)$$

where $\sigma \in \mathbb{R}^{H \times W}$ is the uncertainty of the reconstructed point map, which is also predicted by an additional branch of our VAE decoder. We leave the encoder \mathcal{E} unchanged to modify the latent space as little as possible; instead, we normalize the point maps in the range of $[-1, 1]$ to make them more compatible with the pre-trained image encoder.

Video Conditioning. The original video diffusion model is conditioned on a single image, but here we need to condition it on the entire input video $\mathcal{I} = \{\mathbf{I}^i\}_{i=1}^N$. To this end, we use a hybrid conditioning mechanism using two streams.

As shown in the Fig. 2, in one stream, we extract a

global representation of each frame I^i by passing it to CLIP [64] followed by a lightweight learnable query transformer [1]. These vectors are incorporated in the transformer via cross-attention layers injected in each U-Net block. In the other stream, we extract *local spatial* features from the VAE encoder and concatenate them channel-wise to the noised latents, encoding the generated 4D modalities $\{(\mathbf{D}^i, \mathbf{X}^i, \mathbf{r}^i)\}_{i=1}^N$.

3.3. Multi-Modal Alignment

As noted, Geo4D predicts several non-independent geometric modalities. Furthermore, processing all frames of a long monocular video simultaneously with a video diffusion model is computationally prohibitive. Therefore, during inference, we use a *temporal sliding window* that segments the video into multiple overlapping video clips, with partial overlap to facilitate joining them. The goal of this section is to fuse the resulting multi-modal and multi-window data into a single, coherent reconstruction of the entire video.

Temporal sliding window. Given a video $\mathcal{I} = \{\mathbf{I}^i\}_{i=1}^N$ with N frames, we construct it into several video clips $\mathcal{G} = \{g^k\}, k \in \mathcal{S}$, where each clip g^k contains V frames $\{\mathbf{I}^i\}_{i=k}^{k+V-1}$, and the set of starting indices is $\mathcal{S} = \{0, s, 2s, \dots, \lfloor \frac{N-V}{s} \rfloor s\} \cup \{N-V\}$. Here, s is the sliding window stride. The final term $\{N-V\}$ ensures that the last clip always includes the final frames of the video.

Alignment objectives. First, given the predicted point maps $\mathbf{X}^{i,g}$ for each frame i in each video clip $g \in \mathcal{G}$, we derive corresponding *globally aligned* point maps in world coordinates, as well as the relative camera motion and scale parameters. We denote these quantities with the p subscript to emphasize that they are inferred from the point map predictions. To do so, we extend the pair-wise global alignment loss from DUST3R to a *group-wise* one:

$$\mathcal{L}_p(\mathbf{X}, \lambda_p^g, \mathbf{P}_p^g) = \sum_{g \in \mathcal{G}} \sum_{i \in g} \sum_{uv} \left\| \frac{\mathbf{X}_{uv}^i - \lambda_p^g \mathbf{P}_p^g \mathbf{X}_{uv}^{i,g}}{\sigma_{uv}^{i,g}} \right\|_1, \quad (4)$$

where λ_p^g and $\mathbf{P}_p^g = [\mathbf{R}_p^g \mid \beta_p^g]$ denote the group-wise scale and transformation matrix that align the group-relative point maps $\mathbf{X}^{i,g}$ to the point maps \mathbf{X}^i expressed in the global reference frame. We further parameterize each of these point maps as $\mathbf{X}_{uv}^i = \mathbf{R}_p^{i^\top} \mathbf{K}_p^{i-1} \mathbf{D}_{p,uv}^i(u, v, 1) + \mathbf{o}_p^i$ in terms of each camera's calibration \mathbf{K}_p^i , world-to-camera rotation \mathbf{R}_p^i and center \mathbf{o}_p^i expressed in the global reference frame, and the disparity map \mathbf{D}_p^i . Substituting this expression into the loss function (4) and minimizing it, we can thus recover \mathbf{K}_p^i , \mathbf{R}_p^i , \mathbf{o}_p^i , \mathbf{D}_p^i , λ_p^g , \mathbf{P}_p^g from the predicted point maps.

The steps above thus infer the disparity maps \mathbf{D}_p^i from the point maps, but the model also predicts disparity maps \mathbf{D}_d^i directly, where the d subscript denotes disparity predic-

tion. We introduce the following loss to align them:

$$\mathcal{L}_d(\mathbf{D}_p, \lambda_d^g, \beta_d^g) = \sum_{g \in \mathcal{G}} \sum_{i \in g} \left\| \mathbf{D}_p^i - \lambda_d^g \mathbf{D}_d^{i,g} - \beta_d^g \right\|_1, \quad (5)$$

where λ_d^g and β_d^g are optimized scale and shift parameters.

Finally, the ray maps \mathbf{r} also encode camera pose. To align them with the global camera parameters $(\mathbf{R}_p, \mathbf{K}_p, \mathbf{o}_p)$ obtained from the point map, we first solve an optimization problem to extract the camera parameters from the ray map $\mathbf{r}^{i,g} = \langle \mathbf{d}^{i,g}, \mathbf{m}^{i,g} \rangle$ for each group g at frame i . Following Raydiffusion [114], the camera center $\mathbf{o}_c^{i,g}$ is solved by finding the 3D world coordinate closest to the intersection of all rays:

$$\mathbf{o}_c^{i,g} = \arg \min_{\mathbf{p} \in \mathbb{R}^3} \sum_{u \in H, v \in W} \|\mathbf{p} \times \mathbf{d}_{uv}^{i,g} - \mathbf{m}_{uv}^{i,g}\|^2. \quad (6)$$

The camera extrinsics are solved by optimizing for the matrix \mathbf{H} that transforms the predicted per-pixel ray directions $\mathbf{d}_{uv}^{i,g}$ to the ray directions \mathbf{u}_{uv} of a canonical camera:

$$\mathbf{H}^{i,g} = \arg \min_{\|\mathbf{H}\|=1} \sum_{u \in H, v \in W} \|\mathbf{H} \mathbf{d}_{uv}^{i,g} \times \mathbf{u}_{uv}\|. \quad (7)$$

Then the world-to-camera rotation matrix $\mathbf{R}_c^{i,g}$ and intrinsic matrix $\mathbf{K}_c^{i,g}$ can be solved using the RQ-decomposition of $\mathbf{H}^{i,g}$. Finally, the camera trajectory alignment loss is:

$$\begin{aligned} \mathcal{L}_c(\mathbf{R}_p, \mathbf{o}_p, \mathbf{R}_c^g, \beta_c^g, \lambda_c^g) &= \sum_{g \in \mathcal{G}} \sum_{i \in g} (\|\mathbf{R}_p^{i^\top} \mathbf{R}_c^g \mathbf{R}_c^{i,g} - \mathbf{I}\|_f \\ &\quad + \|\lambda_c^g \mathbf{o}_c^{i,g} + \beta_c^g - \mathbf{o}_p^i\|_2), \end{aligned} \quad (8)$$

where $\mathbf{R}_c^g, \beta_c^g, \lambda_c^g$ are learnable group-wise rotation matrix, translation vector and scale respectively to align the global camera trajectory $(\mathbf{R}_p, \mathbf{o}_p)$ and the predicted ones $(\mathbf{R}_c, \mathbf{o}_c)$. Following MonST3R [113], we also use a loss to smooth the camera trajectory:

$$\mathcal{L}_s(\mathbf{R}_p, \mathbf{o}_p) = \sum_{i=1}^N (\|\mathbf{R}_p^{i^\top} \mathbf{R}_p^{i+1} - \mathbf{I}\|_f + \|\mathbf{o}_p^{i+1} - \mathbf{o}_p^i\|_2). \quad (9)$$

The final optimization objective is the weighted combination of the losses above:

$$\mathcal{L}_{\text{all}} = \alpha_1 \mathcal{L}_p + \alpha_2 \mathcal{L}_d + \alpha_3 \mathcal{L}_c + \alpha_4 \mathcal{L}_s. \quad (10)$$

A note on the invariants. The model predicts point, disparity maps and ray map origins up to scale, as this cannot be uniquely determined from a monocular video. The disparity map is also recovered up to a translation, which discounts the focal length (this is sometimes difficult to estimate due to the dolly zoom effect). Likewise, the ray map origin is recovered up to shift, necessary to allow normalizing these maps.

Category	Method	Sintel [5]		Bonn [55]		KITTI [17]	
		Abs Rel \downarrow	$\delta < 1.25 \uparrow$	Abs Rel \downarrow	$\delta < 1.25 \uparrow$	Abs Rel \downarrow	$\delta < 1.25 \uparrow$
Single-frame depth	Marigold [28]	0.532	51.5	0.091	93.1	0.149	79.6
	Depth-Anything-V2 [106]	0.367	55.4	0.106	92.1	0.140	80.4
Video depth	NVDS [95]	0.408	48.3	0.167	76.6	0.253	58.8
	ChronoDepth [70]	0.687	48.6	0.100	91.1	0.167	75.9
	DepthCrafter* [22]	0.270	69.7	0.071	97.2	0.104	89.6
Video depth & Camera pose	Robust-CVD [32]	0.703	47.8	-	-	-	-
	CasualSAM [116]	0.387	54.7	0.169	73.7	0.246	62.2
	MonST3R [113]	0.335	58.5	0.063	96.4	0.104	89.5
	Ours	0.205	73.5	0.059	97.2	0.086	93.7

Table 1. **Video depth estimation** on Sintel [5], Bonn [55] and KITTI [17] datasets. We follow the evaluation protocols established in recent MonST3R [113] for a fair comparison. Notably, results for DepthCrafter* are reported from its latest version (v1.0.1). The **Best** and the second best results are highlighted.

4. Experiments

4.1. Experimental Settings

Training datasets. Geo4D is trained exclusively on synthetic datasets, yet demonstrates strong generalization to real-world videos. Specifically, we use five synthetic datasets for training: Spring [50], BEDLAM [2], PointOdyssey [119], TarTanAir [93], and VirtualKitti [6]. See the Supp. Mat Tab. 5 for the details.

Training. Our Geo4D is initialized with the weight of Dynamicrafter [102] and trained using AdamW [48] with a learning rate of 1×10^{-5} and a batch size of 32. We use a progressive training strategy to improve convergence and stability. First, we train the model to generate a single geometric modality, *i.e.* the point maps, on a fixed resolution of 512×320 . Next, we introduce the multi-resolution training scheme to improve generalization and robustness, which includes various resolutions: 512×384 , 512×320 , 576×256 , 640×192 . Finally, we progressively add additional geometric modalities, *i.e.*, the ray and depth maps. Training is conducted on 4 NVIDIA H100 GPUs with a total training time of approximately one week.

Inference. As described in Sec. 3.2, given a N -frame video as input, we first split it into overlapping clips \mathcal{G} , each containing $V = 16$ frames, with a stride of $s = 4$. Each video clip, consisting of V frames, is encoded and fed to the diffusion model to sample multi-modal 4D parameters ($\mathbf{X}^{i,g}, \mathbf{D}^{i,g}, \mathbf{r}^{i,g}$) for the video. For sampling, we use DDIM [77] with 5 steps. Finally, the alignment algorithm in Sec. 3.2 is used to fuse the clips into a globally coherent 4D reconstruction of the entire video.

4.2. Video Depth Estimation

Testing data. Our hypothesis is that, despite being trained on synthetic data, our model can generalize well to out-of-distribution synthetic *and* real data as it is based on a pre-trained video diffusion model. To test this hypothe-

sis, we evaluate our model on three benchmarks: Sintel [5] is a synthetic dataset that provides accurate depth annotations, covering diverse scenes with complex camera motion. KITTI [17] is a large driving dataset collected using stereo cameras and LiDAR sensors. Bonn [55] focuses on dynamic indoor scenes. To ensure fair comparisons, we follow the evaluation protocol used by MonST3R [113], where depth sequences are uniformly sampled from the datasets, extracting 50–110 frames per sequence for evaluation.

Metrics. Following the standard affine-invariant depth evaluation protocol [65], we align the predicted video depth with the ground-truth depth before computing metrics. However, unlike single-image depth estimation [28, 105, 106], where depth alignment is performed per frame, we enforce *global scale consistency* by applying a single scale and shift across the entire video sequence. For quantitative evaluation, we adopt two widely used depth metrics: absolute relative error (Abs Rel) and the percentage of inlier points (with a threshold value of $\delta < 1.25$).

Baselines. We compare Geo4D to the state-of-the-art single-frame depth estimation (Marigold [28] and Depth-Anything-V2 [106]), video depth prediction (NVDS [95], ChronoDepth [70] and DepthCrafter [22]), and joint video depth and camera pose prediction (Robust-CVD [32], CasualSAM [116], and MonST3R [113]).

Results. As shown in Table 1, all versions of Geo4D outperform state-of-the-art methods by a large margin. This includes DepthCrafter [22] and MonST3R [113], the most recent video depth diffusion model and the dynamic extension of DUS3d to dynamic scenes, respectively. Notably, while both Geo4D and DepthCrafter are based on the same video diffusion model (Dynamicrafter), our model outperforms DepthCrafter by Abs Rel by 24.0% on Sintel and 17.3% on KITTI datasets despite solving a more general problem. Qualitatively, Fig. 3 shows that Geo4D achieves more consistent results especially for fast moving objects.

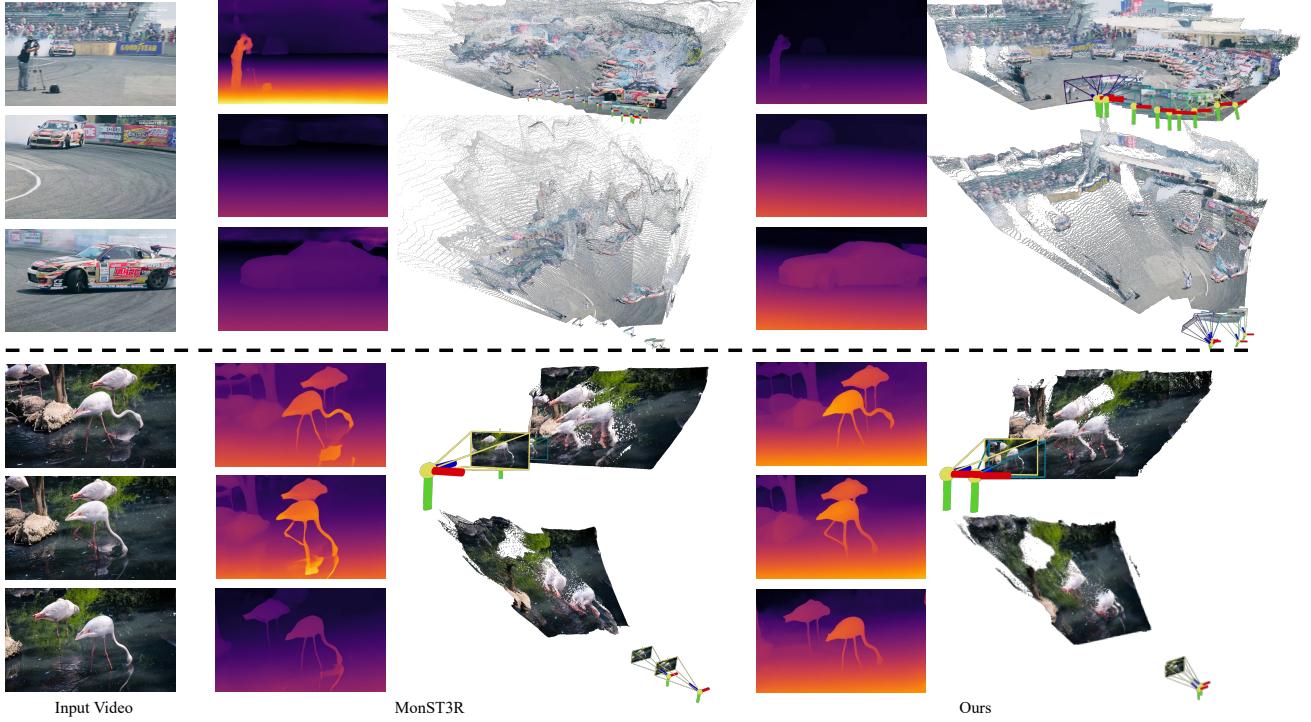


Figure 3. **Qualitative results** comparing Geo4D with MonST3R [113]. Attribute to our group-wise inference manner and prior geometry knowledge from pretrained video diffusion, our model successfully produces consistent 4D geometry under fast motion (first row) and deceptive reflection in the water (second row).

4.3. Camera Pose Estimation

Setup. We evaluate the performance of our Geo4D on both synthetic Sintel [5] dataset and realistic TUM-dynamics [78] dataset. We follow the same evaluation protocol as in MonST3R [113]. Specifically, on Sintel, we select 14 dynamic sequences, and for TUM-dynamics, we sample the first 90 frames of each sequence with a temporal stride of 3. After aligning the predicted camera trajectory with the ground truth one with Umeyama algorithm, we calculate 3 commonly used metrics: Absolute Translation Error (ATE), Relative Translation Error (RPE-T), and Relative Rotation Error (RPE-R). We compare our method with other state-of-the-art discriminative methods, which jointly predict camera pose and depth, including Robust-CVD [32], CausalSAM [116], and MonST3R [113].

Results. To the best of our knowledge, Geo4D is the first method that uses a generative model to estimate the camera parameters in a dynamic scene. As shown in Tab. 2, compared to existing non-generative alternatives, we achieve much better camera rotation prediction (RPE-R) and comparable camera translation prediction (ATE and RPE-T).

4.4. Qualitative Comparison

4D Reconstruction. We compare Geo4D with the state-of-the-art MonST3R method on the DAVIS [23] dataset. Up-

Method	Sintel			TUM-dynamics		
	ATE ↓	RPE-T ↓	RPE-R ↓	ATE ↓	RPE-T ↓	RPE-R ↓
Robust-CVD [32]	0.360	0.154	3.443	0.153	0.026	3.528
CausalSAM [116]	0.141	0.035	0.615	0.071	0.010	1.712
MonST3R [113]	0.108	0.042	0.732	0.063	0.009	1.217
Ours	0.185	0.063	0.547	0.073	0.020	0.635

Table 2. **Quantitative evaluation for camera pose estimation.** We achieve comparable camera pose estimation performance with other discriminative SOTA methods.

grading from pair-wise alignment as in MonST3R to our group-wise alignment improves temporal consistency, leading to a more stable and globally coherent 4D reconstruction of point maps and camera trajectory, particularly in highly dynamic scenes. As shown in the top row in Fig. 3, Geo4D successfully tracks in 4D the racing car, whereas MonST3R struggles due to the rapid motion between pairs of images. Furthermore, probably because of the strong prior captured by the pre-trained video generative model, Geo4D correctly reconstructs the reflection of the flamingo in the water (second row in Fig. 3), whereas MonST3R misinterprets the reflection as a foreground object, resulting in incorrect depth.

Video Depth Prediction. We compare Geo4D with state-of-the-art video depth predictors MonST3R [113] and DepthCrafter [22] on Sintel [5] dataset. Qualitatively, Geo4D produces more detailed geometry, for instance for

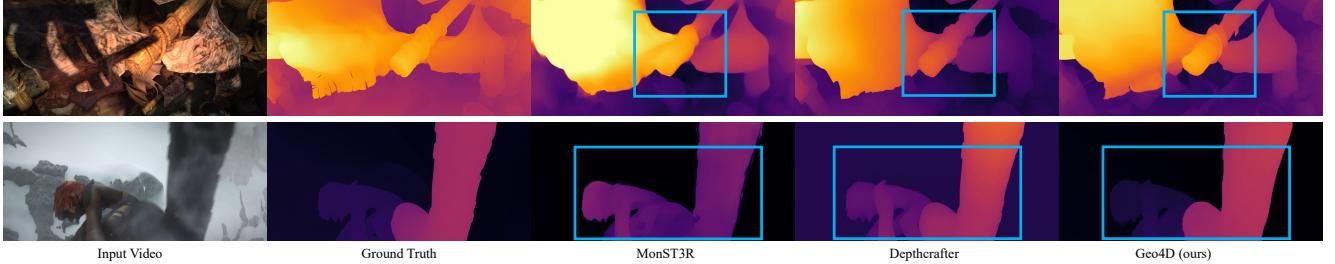


Figure 4. **Qualitative video depth results** comparing Geo4D with MonST3R [113] and DepthCrafter [22]. Owing to our proposed multi-modal training and alignment, as well as the prior knowledge from diffusion, our method can infer a more detailed structure (first row) and a more accurate spatial arrangement from video (second row).

Training			Inference			Video Depth		Camera Pose		
Point Map	Depth Map	Ray Map	Point Map	Depth Map	Ray Map	Abs Rel ↓	$\delta < 1.25 \uparrow$	ATE ↓	RPE trans ↓	RPE rot ↓
✓	-	-	✓	-	-	0.232	71.3	0.335	0.076	0.731
✓	✓	✓	✓	-	-	0.223	72.5	0.237	0.070	0.566
✓	✓	✓	-	✓	-	0.211	73.4	-	-	-
✓	✓	✓	-	-	✓	-	-	0.268	0.192	1.476
✓	✓	✓	✓	✓	✓	0.205	73.5	0.185	0.063	0.547

Table 3. **Ablation study for the different modalities of the geometric representation** on the Sintel [5] dataset. We demonstrate the effectiveness of our key design choices that both leverage multi-modality as additional training supervision signal and postprocess through our proposed multi-modal alignment algorithm will improve the overall performance.

Stride	s / frame	Video Depth		Camera Pose		
		Abs Rel ↓	$\delta < 1.25 \uparrow$	ATE ↓	RPE trans ↓	RPE rot ↓
15	0.92	0.213	72.4	0.210	0.092	0.574
8	1.24	0.212	72.8	0.222	0.074	0.524
4	1.89	0.205	73.5	0.185	0.063	0.547
2	3.26	0.204	72.9	0.181	0.058	0.518

Table 4. **Ablation study for the temporal sliding window stride** on the Sintel [5] dataset. Smaller strides are better.

the rope on the stick in the first row of Fig. 4, and a better spatial arrangement between different dynamic objects, as shown the second row of Fig. 4.

4.5. Ablation Study

We ablate our key design choices and the effect of different modalities on the Sintel dataset.

We study the effect of multi-modality in Tab. 3. The three modalities, *i.e.* point map, depth map, and ray map, and can be used either at training or inference time, or both. The first two rows show that the diffusion model trained with point maps as a single modality performs worse in both video depth and camera pose estimation than the diffusion model trained with all three modalities. Therefore, the other two modalities, even if they can be seen as redundant, serve as additional supervisory signal during training, which improves the generalization ability of the diffusion model.

We then investigate the effectiveness of our multi-modal alignment algorithm. Compared with the second to the fourth row in Tab. 3, which leverage only a single modality during inference, multi-modal alignment optimization (last row) achieves the best performance, showing the benefits of fusing the multiple modalities at inference time.

We ablate the sliding window stride in Tab. 4. Results

improve with a shorter stride, in part because this means that more windows and estimates are averaged, reducing the variance of the predictions by the denoising diffusion model, which is stochastic. We choose stride $s = 4$ for our main results to balance the runtime and the performance. Note that MonST3R [113] requires 2.41 seconds to process one frame under the same setting. So, our method is 1.27 times faster than MonST3R [113].

5. Discussion and Conclusion

We have introduced Geo4D, a novel approach that adapts a video generator to dynamic 4D reconstruction. By building on a pre-trained video generator, Geo4D achieves excellent generalization to real data despite being trained only on 4D synthetic data. We have also shown the benefits of predicting multiple modalities and fusing them at test time via optimization. Our model outperforms state-of-the-art methods on video depth and camera rotation prediction, particularly on challenging dynamic scenes.

Despite these successes, our approach has limitations, one of which is that the point map encoder-decoder is still not entirely accurate, and that, in turn, is a bottleneck on the overall reconstruction quality.

Our approach also opens a path to integrating 4D geometry in video foundation models, *e.g.*, to generate 3D animations from text, or to provide a more actionable signal when the video model is used as a proxy for a world model.

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Geo4D: Leveraging Video Generators for Geometric 4D Scene Reconstruction

Supplementary Material

In this **supplementary document**, we provide additional materials to supplement our main submission. In the **supplementary video**, we show more visual results using our method. The **code** will be made publicly available for research purposes.

6. Implementation details

6.1. Training dataset

As shown in Tab. 5, we use five synthetic datasets for training: Spring [50], BEDLAM [2], PointOdyssey [119], Tar-TanAir [93], and VirtualKITTI [6]. Although all datasets we used are synthetic data sets, we found that there are still some missing depth pixels in PointOdyssey [119]. So we apply max pooling to inpaint those missing pixels. During training, we sample each data set with the corresponding ratio in Tab. 5. For each sample, we sample 16 frames from the sampled sequence with the sampling stride randomly chosen from $\{1, 2, 3\}$ to allow our diffusion model to adapt to different input videos with various FPS.

6.2. Optimization details

The overall optimization process is outlined in Algorithm 1. We first predict all three modality maps using our diffusion model for each video clip g . The predicted point maps are then roughly aligned based on the overlapping frames using the Umeyama algorithm [84]. The camera intrinsic \mathbf{K}^k is initialized by minimizing the projection error of the point map $\mathbf{X}^{k,g}$ in its reference (first) frame k within each window group g^k . The camera extrinsics are then initialized using the RANSAC PnP algorithm. In the first stage of optimization, the point maps are roughly disentangled into camera pose and depth map. The disparity map is then aligned with the global depth inferred from point maps by solving Eq. (5) to obtain the scale and shift parameters. The camera parameters extracted from the predicted ray map are aligned with the global camera trajectory based on the reference (first) frame of each video clip g via Eq. (8). After initializing all the alignment learnable parameter including rotation \mathbf{R}_*^g , scale λ_*^g , and shift β_*^g across different modality, where $* \in \{p, d, c\}$, we jointly optimize all the learnable parameters by Eq. (10).

6.3. Ablation study for number of denoising steps

We study the influence of the number of denoising steps during inference. As shown in Tab. 6, the model achieves optimal performance around steps equal to 5. Compared to the video generation task, where a larger denoising step usually produces a more detailed generated video, 4D recon-

Algorithm 1 Multi-Modal Alignment Optimization

```

1:  $\mathbf{X}^{i,g}, \mathbf{D}^{i,g}, \mathbf{r}^{i,g} \leftarrow$  Predicted by our diffusion model
2:  $\mathbf{D}_p^i, \lambda_p^g, \mathbf{R}_p^g, \beta_p^g \leftarrow$  Initialized by Umeyama algorithm
3:  $\mathbf{K}_p^k \leftarrow$  Optimized from  $\mathbf{X}^{k,g^k}$ 
4:  $\mathbf{R}_p^i, \mathbf{o}_p^i \leftarrow$  Initialized by Ransac PnP from pointmaps  $\mathbf{X}^i$ 
5:  $\mathbf{R}_c^{i,g}, \mathbf{o}_c^{i,g} \leftarrow$  Initialized by Eqs. (6) and (7) from raymaps  $\mathbf{r}^{i,g}$ 
6: repeat
7:   if Iteration = Align start iteration then
8:      $\lambda_d^g, \beta_d^g \leftarrow \arg \min \mathcal{L}_d$  (Eq. (5))
9:      $\mathbf{R}_c^g, \lambda_c^g, \beta_c^g \leftarrow \arg \min \mathcal{L}_c$  (Eq. (8))
10:    else if Iteration < Align start iteration then
11:       $\mathbf{D}_p^i, \mathbf{K}_p^i, \mathbf{R}_p^i, \mathbf{o}_p^i, \lambda_p^g, \mathbf{R}_p^g, \beta_p^g \leftarrow \arg \min \mathcal{L}_p + \mathcal{L}_s$ 
12:    else
13:       $\mathbf{D}_p^i, \mathbf{K}_p^i, \mathbf{R}_p^i, \mathbf{o}_p^i, \lambda_*^g, \mathbf{R}_*^g, \beta_*^g \leftarrow \arg \min \mathcal{L}_{\text{all}}$ 
14:    end if
15: until max loop reached

```

Dataset	Scene type	#Frames	#Sequences	Ratio
PointOdyssey [119]	Indoors/Outdoors	200K	131	16.7%
TartanAir [93]	Indoors/Outdoors	1000K	163	16.7%
Spring [50]	Outdoors	6K	37	16.7%
VirtualKITTI [6]	Driving	43K	320	16.7%
BEDLAM [2]	Indoors/Outdoors	380K	10K	33.3%

Table 5. **Details of training datasets.** Our method only uses synthetic datasets for training.

Steps	Video Depth		Camera Pose		
	Abs Rel \downarrow	$\delta < 1.25 \uparrow$	ATE \downarrow	RPE trans \downarrow	RPE rot \downarrow
1	0.221	70.7	0.234	0.072	0.753
5	0.205	73.5	0.185	0.063	0.547
10	0.207	73.2	0.212	0.071	0.508
25	0.220	72.2	0.211	0.074	0.564

Table 6. **Ablation study for the DDIM sampling steps.** on the Sintel [5] dataset.

Method	Video Depth		Camera Pose		
	Abs Rel \downarrow	$\delta < 1.25 \uparrow$	ATE \downarrow	RPE trans \downarrow	RPE rot \downarrow
w/o fine-tuned	0.212	72.1	0.192	0.061	0.577
w fine-tuned	0.205	73.5	0.185	0.063	0.547

Table 7. **Ablation study for the fine-tuned point map VAE** on the Sintel [5] dataset. The fine-tuned point map VAE performs better than the original one.

struction is a more deterministic task, which requires fewer steps. Similar phenomena are also observed in [22], which utilize a video generator for the video depth estimation task.

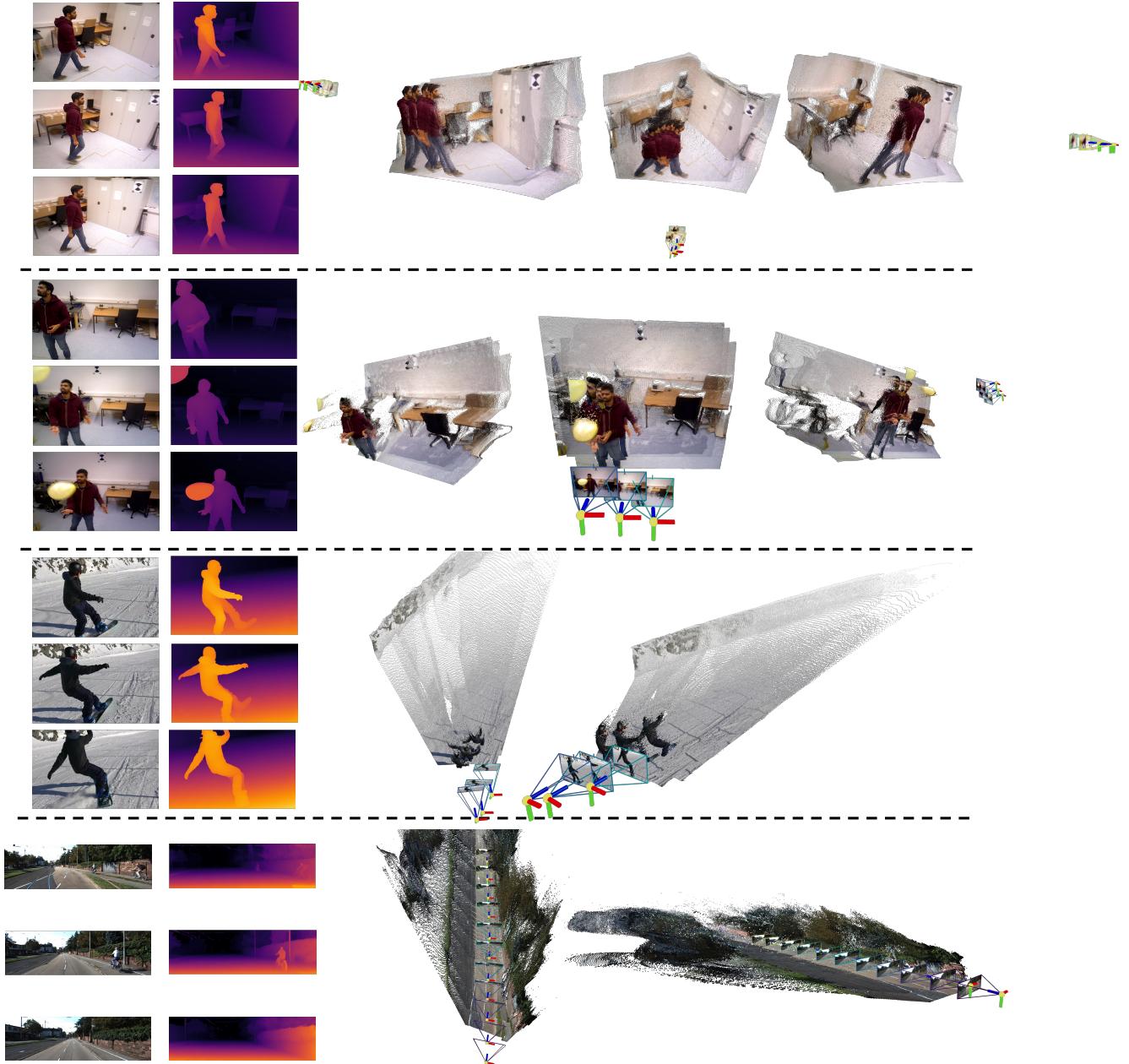


Figure 5. **Additional qualitatively results.** Our method generalizes well to various scenes with different 4D objects and performs robustly against different camera and object motion.

6.4. Ablation study for fine-tuned point map VAE

As stated in the main paper, we added an additional branch to predict the uncertainty for our point map VAE and fine-tuned it based on Eq. 3. We perform the ablation study on our fine-tuning strategy. As shown in Tab. 7, our fine-tuned point map VAE achieves consistent better performance on both video depth estimation and camera pose estimation tasks compared with the original pre-trained image VAE,

demonstrating the necessity and the effectiveness of our fine-tuning strategy.

7. Visualization

As shown in Fig. 5, we show additional visualization results for both the indoor, outdoor, and driving scene. Although our model is only trained on synthetic datasets, it is generalized to real-world data with diverse objects and motions.