

Uni3C: Unifying Precisely 3D-Enhanced Camera and Human Motion Controls for Video Generation

CHENJIE CAO, Alibaba DAMO Academy, Fudan University, Hupan Lab, China

JINGKAI ZHOU, Alibaba DAMO Academy, Hupan Lab, China

SHIKAI LI, Alibaba DAMO Academy, Hupan Lab, China

JINGYUN LIANG, Alibaba DAMO Academy, Hupan Lab, China

CHAOHUI YU*, Alibaba DAMO Academy, Hupan Lab, China

FAN WANG, Alibaba DAMO Academy, China

YANWEI FU†, Fudan University, Shanghai Innovation Institute, China

XIANGYANG XUE, Fudan University, China

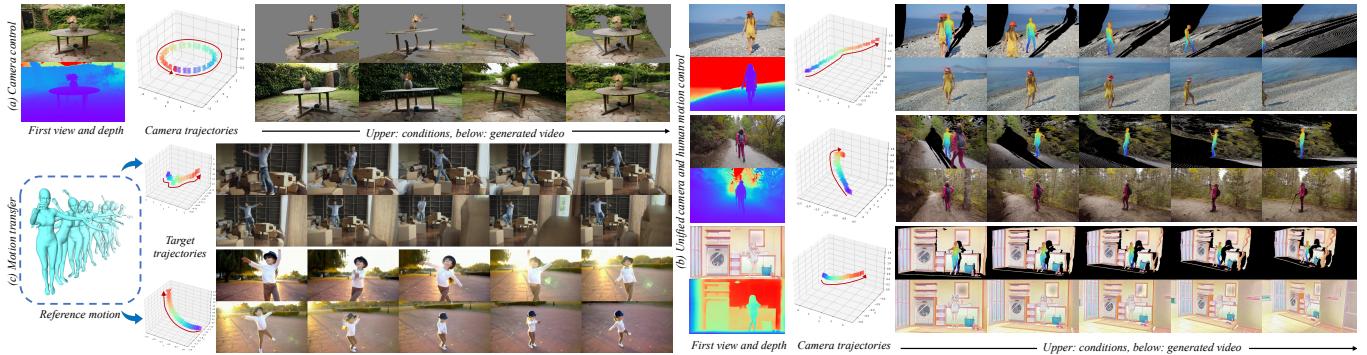


Fig. 1. Given a single-view image across various domains (e.g., real-world, text-to-image, animation), we first extract the monocular depth and focal length of it via Depth-Pro [Bochkovskii et al. 2024] and then achieve point clouds. Then, the proposed Uni3C can generate impressive videos under arbitrary (a) camera trajectories, (b) human motion characters (SMPL-X [Pavlakos et al. 2019]), or both of these conditions. (c) Uni3C further supports the camera-controlled motion transfer. Please review the videos in the supplementary for more details.

Camera and human motion controls have been extensively studied for video generation, but existing approaches typically address them separately, suffering from limited data with high-quality annotations for both aspects. To overcome this, we present Uni3C, a unified 3D-enhanced framework for precise control of both camera and human motion in video generation. Uni3C includes two key contributions. First, we propose a plug-and-play control module trained with a frozen video generative backbone, PCDController, which utilizes unprojected point clouds from monocular depth to achieve

*Project lead.

†Corresponding author. Prof. Yanwei Fu is with the Institute of Trustworthy Embodied AI, and the School of Data Science, Fudan University.

Authors' Contact Information: Chenjie Cao, Alibaba DAMO Academy, Fudan University, Hupan Lab, China, ccjdurandal422@163.com; JingKai Zhou, Alibaba DAMO Academy, Hupan Lab, China; ShiKai Li, Alibaba DAMO Academy, Hupan Lab, China; JingYun Liang, Alibaba DAMO Academy, Hupan Lab, China; ChaoHui Yu, Alibaba DAMO Academy, Hupan Lab, China; Fan Wang, Alibaba DAMO Academy, China; Yanwei Fu, Fudan University, Shanghai Innovation Institute, China, yanweifu@fudan.edu.cn; XiangYang Xue, Fudan University, China.

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accurate camera control. By leveraging the strong 3D priors of point clouds and the powerful capacities of video foundational models, PCDController shows impressive generalization, performing well regardless of whether the inference backbone is frozen or fine-tuned. This flexibility enables different modules of Uni3C to be trained in specific domains, *i.e.*, either camera control or human motion control, reducing the dependency on jointly annotated data. Second, we propose a jointly aligned 3D world guidance for the inference phase that seamlessly integrates both scenic point clouds and SMPL-X characters to unify the control signals for camera and human motion, respectively. Extensive experiments confirm that PCDController enjoys strong robustness in driving camera motion for fine-tuned backbones of video generation. Uni3C substantially outperforms competitors in both camera controllability and human motion quality. Additionally, we collect tailored validation sets featuring challenging camera movements and human actions to validate the effectiveness of our method. Codes are released at <https://github.com/alibaba-damo-academy/Uni3C>.

CCS Concepts: • Networks → Network algorithms; • Computing methodologies → Computer vision.

Additional Key Words and Phrases: Camera control, Human animation, Video generation, Generative models

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1 Introduction

Recent advancements in foundational video diffusion models (VDMs) [Blattmann et al. 2023; Brooks et al. 2024; Kong et al. 2024; Kuaishou 2024; RunwayML 2024; Wang et al. 2025a; Yang et al. 2025] have unlocked unprecedented capabilities in creating dynamic and realistic video content. A significant challenge in this field is achieving controllable video generation, a feature with broad applications in virtual reality, film production, and interactive media. In this paper, we focus on two aspects of controllable video generation: camera control [Bahmani et al. 2025a; He et al. 2025a; Ren et al. 2025; Yang et al. 2024; Yu et al. 2024; Zheng et al. 2025a] and human motion control [Hu 2024; Hu et al. 2025; Tan et al. 2025; Wang et al. 2024a; Xu et al. 2024b; Zhou et al. 2024]—both of which are critical and interdependent in real-world scenarios.

Recent pioneering works have extensively studied controlling camera trajectories for VDMs through explicit conditions like Plücker ray [Bahmani et al. 2025a; He et al. 2025a,b; Liang et al. 2024; Zheng et al. 2025a], point clouds [Feng et al. 2025; Li et al. 2025b; Popov et al. 2025; Ren et al. 2025; Yu et al. 2024]. Concurrently, controllable human animation also attracted a lot of attention based on poses [Hu 2024; Hu et al. 2025; Tan et al. 2025; Xu et al. 2024b] or SMPL characters [Zhou et al. 2024, 2025b; Zhu et al. 2024]. Despite these advancements, several challenges remain: 1) Most approaches deeply hack the inherent capacities of VDMs, which have been trained with domain-specific data and conditions, inevitably undermining the generalization to handle out-of-distribution scenarios. 2) Very few works investigate the joint control of both camera trajectories and human motions. This requires diverse camera trajectories in human-centric videos with high-quality annotations [Wang et al. 2024a], which are often expensive to obtain. 3) There is a lack of explicit and synchronized guidance that incorporates strong 3D-informed priors to control both camera movements and human motions concurrently. Relying on separate conditions, like point clouds and SMPL, struggles to represent physically reasonable interactions and positional relations between characters and environments, resulting in conflicting guidance and suboptimal outcomes.

To address these challenges, we present **Uni3C**, a novel framework that **Unifies** precise 3D-enhanced camera and human motion Controls for video generation as shown in Figure 1 via two key innovations. Firstly, we propose the insight that controlling camera trajectories for powerful foundational VDMs can be achieved by lightweight, trainable modules with *rich informed guidance* and *reasonable training strategies*. By avoiding hacking the underlying capacities of VDMs, our camera-controlling model can be directly generalized to versatile downstream tasks rather than costly joint training and extensive Structure from Motion (SfM) labeling [Li et al. 2025a; Schönberger et al. 2016; Zhao et al. 2022]. Secondly, we claimed that camera and human motion controls are inherently interdependent. Therefore, we propose to align their conditions into a *global 3D world* during the inference phase, enabling 3D consistent generation across both domains.

Formally, our Uni3C is built upon the foundational VDM–Wan2.1 [Wang et al. 2025a]. For the control of camera trajectories, we propose PCDController, a plug-and-play control module with only 0.95B parameters (compared to 14B of Wan2.1) that operates on unprojected 3D point clouds derived from monocular depth estimation [Bochkovskii et al. 2024]. Thanks to the rich geometric priors of point clouds, PCDController is capable of fine-grained camera control, even when trained on constrained multi-view images and videos with a frozen backbone. Furthermore, PCDController can be compatible with fine-tuned VDM backbones for versatile downstream tasks. This surprising factor supports domain-specific training, *i.e.*, camera and human motion modules can be trained independently without jointly annotated data. For the global 3D world guidance, we align scenic point clouds (for camera control) and SMPL-X characters [Pavlakos et al. 2019] (for human animation) into the same world-coordinate space via the rigid transformation [Umeyama 1991], while the 2D keypoints [Xu et al. 2023] bridge the relation of two presentations. Note that our alignment enables complicated motion transfer, covering disparate characters, positions, and viewpoints as verified in the last row of Figure 1.

Extensive experiments validate the efficacy of Uni3C. To evaluate the remarkable generalization of PCDController, we collect an out-of-distribution test set across different domains, where each image has four different camera trajectories. For the joint controllability, we build a comprehensive test set of in-the-wild human videos. GVHMR [Shen et al. 2024] is used to extract SMPL-X as the condition, while three complex and random camera trajectories are assigned for each video. VBench++ [Huang et al. 2024] is employed to verify the overall performance of our method. Uni3C significantly outperforms other competitors, both quantitatively and qualitatively.

We highlight the key contributions of Uni3C as:

- **PCDController.** A robust, lightweight camera control module is proposed, which enjoys strong 3D priors from point clouds, compatible with both frozen or adapted VDMs.
- **Global 3D World Guidance.** A unified inference framework that aligns scene geometry (point clouds) and human characters (SMPL-X) for 3D-coherent video control.
- **Comprehensive Validation.** We propose new benchmarks and datasets to evaluate challenging camera-human interaction scenarios, demonstrating Uni3C’s superiority over existing approaches.

2 Related Work

2.1 Camera Control for VDMs

Controlling camera trajectories in video generation has garnered significant attention recently. Some works focused on injecting camera parameters into VDMs to achieve camera controllability [Bahmani et al. 2025a,b; He et al. 2025a,b; Liang et al. 2024; Wang et al. 2024b; Zheng et al. 2025a], typically utilizing the Plücker ray presentation. For instance, VD3D [Bahmani et al. 2025b] designed a tailored framework for Diffusion Transformer (DiT) [Peebles and Xie 2023], while AC3D [Bahmani et al. 2025a] further emphasized the generalization with fewer trainable parameters. Moreover, DimensionX [Sun et al. 2024] further decoupled the spatial and temporal control with different LoRAs [Hu et al. 2022]. Despite the progress made by these

methods, they cannot control the camera movements precisely, particularly when the case is beyond the training domains with an unknown metric scale. Thus, other recent works have employed point cloud conditions via training-based [Feng et al. 2025; Li et al. 2025b; Popov et al. 2025; Ren et al. 2025; Yu et al. 2024] and training-free [Hou et al. 2025; You et al. 2025] manners. However, they fail to accommodate the generalized model design and training strategy to handle imperfect point clouds or out-of-distribution data, especially in motional scenarios involving humans or animals.

2.2 Unified Control for VDMs

Recent works have unified multiple conditions to guide video generation [Chen et al. 2025; Feng et al. 2025; Geng et al. 2025; Gu et al. 2025; Wang et al. 2024a,b; Zheng et al. 2025b]. MotionCtrl [Wang et al. 2024b] integrated the camera and object motion controls through separate pose and trajectory injections. Subsequently, researchers further explored the presentation of conditions, such as point trajectories [Feng et al. 2025], point tracking [Geng et al. 2025; Gu et al. 2025], and 3D-aware signals [Chen et al. 2025]. Moreover, VidCraft3 [Zheng et al. 2025b] considered the lighting control to VDMs for the first time. For the control of both cameras and human motions, some works focus on the behavior transfer based on camera and human motion estimation [Jiang et al. 2024; Kocabas et al. 2024]. Humanvid [Wang et al. 2024a] first unified them in video generation. However, it requires both camera and human guidance from the same source video; otherwise, the human pose would conflict with the camera movements, leading to limited flexibility for the decoupled control. Despite the promising performance demonstrated by these pioneering approaches, they often rely heavily on joint training under various conditions and well-labeled datasets. Furthermore, there has been limited discussion on unified control within foundational VDMs that exceed 10B parameters. Our work offers a solution to address these issues: unifying existing models for different downstream tasks without the need for costly fine-tuning or fully annotated datasets. This strategy is particularly well-suited for large VDMs, enabling models to focus more on enhancing performance within their specific domains.

3 Preliminary: Video Diffusion Models

We briefly review VDMs and Wan2.1 [Wang et al. 2025a] in this section as preliminary knowledge. VDMs are mainly based on the latent diffusion model [Rombach et al. 2022], modeling the conditional distribution $p(z_0|c_{txt}, c_{img})$, where z_0 indicate clean video latent features encoded by 3D-VAE; c_{txt} , c_{img} denote the text condition for Text-to-Video (T2V) and the optional image condition for Image-to-Video (I2V), respectively. The training of VDM involves reversing the diffusion process by the noise estimator ϵ_θ as:

$$\min_{\theta} \mathbb{E}_{z_0, t, \epsilon, c_{txt}, c_{img}} [\|\epsilon_\theta(z_t, t, c_{txt}, c_{img}) - \epsilon\|^2], \quad (1)$$

where $\epsilon \sim \mathcal{N}(0, I)$ indicates Gaussian noise; timestep $t \in [0, T_{max}]$; z_t is the intermediate noisy latent state of timestep t . Recently, most VDMs have employed Flow Matching (FM) [Lipman et al. 2022] as the improved diffusion process with faster convergence and more stable training. Based on the ordinary differential equations (ODEs), FM formulates the linear interpolation between z_0 and z_1 ,

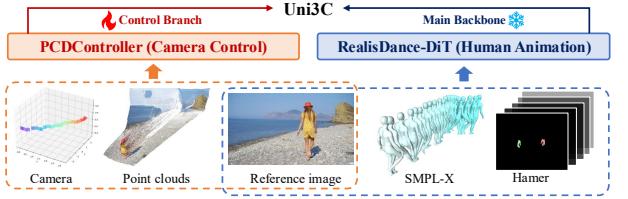


Fig. 2. **The overview of Uni3C**, which adopts multi-modal conditions. The camera, point clouds, and reference image are assigned to the camera control module called PCDCController, while the reference image, SMPL-X [Pavlakos et al. 2019], and Hamer [Pavlakos et al. 2024] are assigned to human animation called RealisDance-DiT [Zhou et al. 2025b].

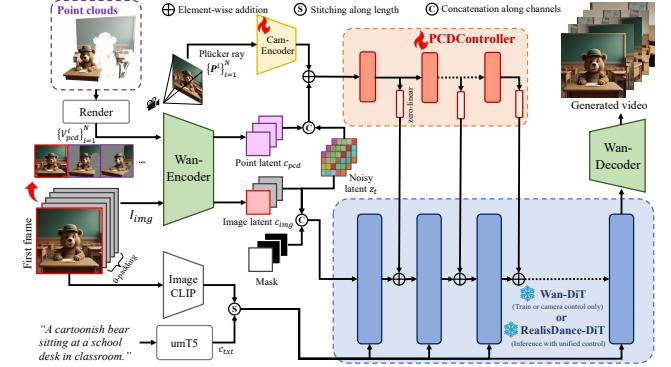


Fig. 3. **Pipeline of PCDCController**, which is built as a lightweight DiT trained from scratch. We first obtain point clouds via monocular depth from the first view. Then, the point clouds are warped and rendered into the video V_{pcd} . Input conditions for PCDCController comprise rendered V_{pcd} , Plucker ray P , and the noisy latent z_t . Only the PCDCController and camera encoder are trainable in our framework. For inference of unified control over camera and human motions, we directly replace the frozen Wan backbone with RealisDance-DiT [Zhou et al. 2025b] without joint fine-tuning.

i.e., $z_t = tz_1 + (1-t)z_0$, where $t \in [0, 1]$ is sampled from the logit-normal distribution. The velocity prediction v_θ is written as:

$$\min_{\theta} \mathbb{E}_{z_0, t, \epsilon, c_{txt}, c_{img}} [\|v_\theta(z_t, t, c_{txt}, c_{img}) - v_t\|^2], \quad (2)$$

where the ground truth velocity denotes $v_t = \frac{dz_t}{dt} = z_1 - z_0$. Additionally, recent foundational VDMs [Brooks et al. 2024; Kong et al. 2024; Wang et al. 2025a; Yang et al. 2025] are built with DiT [Peebles and Xie 2023] to achieve more capacities for video generation.

Wan2.1 [Wang et al. 2025a] is an open-released VDM with DiT architecture trained with flow matching [Lipman et al. 2022]. umT5 [Chung et al. 2023] is utilized as the multi-language text encoder to inject textual features into Wan2.1 through cross-attention. For image-to-video, Wan-I2V further incorporates features from CLIP’s image encoder [Radford et al. 2021] to improve the results. Uni3C is primarily designed for Wan-I2V with 14B parameters, but we empirically find that it is compatible with the Wan-T2V version as verified in Section 5.4, showing convincing generalization.

4 Method

Overview. We first present the overview of Uni3C in Figure 2. Given a reference view $I_{img} \in \mathbb{R}^{3 \times h \times w}$, camera trajectories $\{c_{cam}^i\}_{i=1}^N$ of N target views, and textual condition, Uni3C uses PCDCController

to produce the target video under specified camera trajectories. This process can be formulated as $p(z_0|c_{txt}, c_{img}, c_{cam})$, where z_0 indicates the clean latent video feature, c_{txt}, c_{img} are textual features from umT5 and image latent condition encoded from I_{img} , respectively. We show the pipeline of PCDController in Figure 3 as a core component of Uni3C for generalized camera control (Section 4.1) across downstream tasks. In this work, we focus on human animation (Section 4.2). Subsequently, we introduce the global 3D world guidance illustrated in Figure 5 to unify both camera and human characters into a consistent 3D space for inference (Section 4.3).

4.1 PCDController with 3D Geometric Priors

Architecture. Following AC3D [Bahmani et al. 2025a], PCDController is designed within a simplified DiT module rather than copying modules and weights from the main backbone as ControlNet [Zhang et al. 2023]. To preserve the generalization of Wan-I2V, we follow the insight of *training as few parameters as possible once the effective camera control has been achieved*. Formally, we reduce the hidden size of PCDController from 5120 to 1024, while zero-initialized linear layers are used to project the hidden size back to 5120 before being added to Wan-I2V. Moreover, as investigated in [Bahmani et al. 2025a; Liang et al. 2024], VDMs mainly determine camera information through shallow layers. Thus, we only inject camera-controlling features into the first 20 layers of Wan-I2V to further simplify the model. Additionally, we discard the textual condition for PCDController to alleviate intractable hallucination and remove all cross-attention modules. In this way, the overall number of trainable parameters for PCDController is reduced to 0.95B, a significant reduction compared to Wan-I2V (14B).

3D Geometric Priors. In contrast to merely utilizing Plücker ray as the camera embedding [Bahmani et al. 2025a; Liang et al. 2024], we incorporate much stronger 3D geometric priors to compensate the model simplification, i.e., videos $\{V_{pcd}^i\}_{i=1}^N \in \mathbb{R}^{N \times 3 \times h \times w}$ rendered from point clouds under given camera trajectories. Specifically, we first use Depth-Pro [Bochkovskii et al. 2024] to extract the monocular depth map from the reference view. We then align this depth map into a metric representation using SfM annotations [Schönberger et al. 2016] or multi-view stereo [Cao et al. 2024]. Following [Cao et al. 2025], we employ RANSAC to derive the rescale and shift coefficients, preventing the collapse of constant depth outcomes. Subsequently, the point clouds $X_{pcd} \in \mathbb{R}^{h \times w \times 3}$ are got by unprojecting all 2D pixels from I_{img} into the world coordinate via its metric depth \hat{D}_{img} as follows:

$$X_{pcd}(x) \simeq R_{c \rightarrow w} \hat{D}_{img}(x) K^{-1} \hat{x}, \quad (3)$$

where x denotes the 2D coordinates of I_{img} , while \hat{x} refers to the homogeneous coordinates; $K, R_{c \rightarrow w}$ mean the intrinsic and extrinsic cameras of the reference view, respectively. After that, we render $\{V_{pcd}^i\}_{i=2}^N$ for the remaining $(N - 1)$ views by PyTorch3D according to their respective camera intrinsics and extrinsics. Note that the first rendering corresponds to the reference image, i.e., $V_{pcd}^1 = I_{img}$, to confirm the identity. We apply V_{pcd} to the 3D-VAE of Wan2.1 to achieve c_{pcd} as the point latent condition. To further handle the significant viewpoint changes, which may extend beyond the point clouds' visibility of the first frame, PCDController also includes



Fig. 4. **Results of PCDController with imperfect point clouds.** Benefiting from the well-preserved capacity of VDM, PCDController enjoys robust generation with inferior point clouds.

Plücker ray embedding [Xu et al. 2024a], $\{\mathbf{P}^i\}_{i=1}^N \in \mathbb{R}^{N \times 6 \times h \times w}$, as the auxiliary condition. $\{\mathbf{P}^i\}_{i=1}^N$ is encoded by a small camera encoder, comprising causal convolutions and a 4-8-8 downsampling factor to keep the same sequential length as 3D-VAE outputs. The distribution modeling of PCDController is $p(z_0|c_{txt}, c_{img}, c_{pcd}, \mathbf{P})$.

Discussion. We empirically find that our method demonstrates robust performance even when working with imperfect point clouds obtained through monocular depth unprojection. In this context, the point clouds serve as the primary camera control signal, facilitating the convergence of training rather than dominating the multi-view geometric and textural generations, as illustrated in Figure 4. Moreover, the lightweight PCDController retains its precise camera control capability *over versatile fine-tuned Wan backbones, even without joint training*. This flexibility allows for a range of downstream applications, showcasing the robustness of our approach.

4.2 Human Animation

In this paper, we explore the unified control through two human animation approaches, both of which are built on the Wan2.1 framework, targeting I2V and T2V, respectively. While these methods are not the primary focus of our work, we provide a brief introduction here. Formally, the concurrently pioneering work, RealisDance-DiT [Zhou et al. 2025b], directly replaces the Wan-I2V backbone for high-quality human animation during inference. RealisDance-DiT incorporates SMPL-X [Pavlakos et al. 2019] and Hamer [Pavlakos et al. 2024] as additional input conditions through newly zero-initialized layers to guide human motions, while camera-control features are added via the external PCDController as shown in Figure 2. To ensure the flexibility for motion transfer, RealisDance-DiT randomly selects the reference frame in the video sequence, which is not perfectly aligned with the given SMPL-X. RealisDance-DiT only trains self-attention modules and patchify encoders to confirm the generalization. However, we clarify that integrating the control branch trained within different backbones is still challenging, requiring a generalized control branch like our proposed PCDController. Furthermore, we tried another version, RealisDance-DiT-T2V, based on Wan-T2V without reference image conditions to explore the generalization of PCDController. Remarkably, PCDController adapts successfully to Wan-T2V, empowering it with impressive I2V ability.

4.3 Global 3D World Guidance

Definition. As illustrated in Figure 2, Uni3C adopts multi-modal conditions, including camera, point clouds, reference image, SMPL-X [Pavlakos et al. 2019], and Hamer [Pavlakos et al. 2024]. The first three conditions are used for PCDController, while the latter three

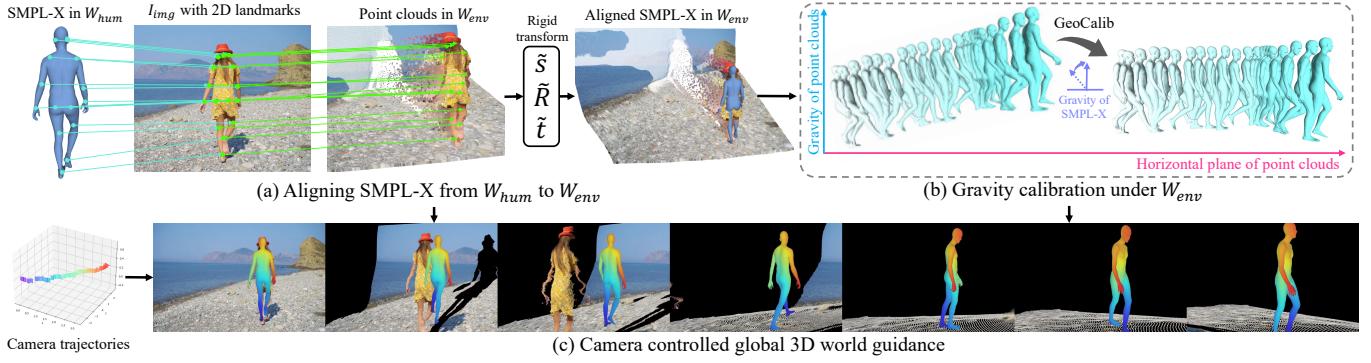


Fig. 5. **Overview of global 3D world guidance.** (a) We first align SMPL-X characters from the human world space W_{hum} to the environment world space W_{env} with dense point clouds. (b) GeoCalib [Veicht et al. 2024] is used to calibrate the gravity direction of SMPL-X. (c) Rigid transformation coefficients $\tilde{s}, \tilde{R}, \tilde{t}$ are employed to align the whole SMPL-X sequence. We re-render all aligned conditions under specific camera trajectories as the global 3D world guidance.

are used for human animations. We employ GVHMR [Shen et al. 2024] to recover SMPL-X characters. One can also retrieve desired motion sequences from motion datasets [Guo et al. 2022; Lin et al. 2023; Plappert et al. 2016; Punnakkal et al. 2021] or generate new motions through text-to-motion models [Barquero et al. 2024; Guo et al. 2024; Jiang et al. 2023]. Although most of the conditions above are formulated as 3D presentations, they stay in two different world coordinates. We define the point cloud world coordinate as the **environmental world space** W_{env} , which is the main world space controlled by cameras, while the SMPL-X is placed in the **human world space** W_{hum} . It is non-trivial to control the camera across two different world spaces consistently. For example, determining the initial camera position within W_{hum} is particularly ambiguous, especially for tasks involving motion transfer. Moreover, to facilitate flexible control over separate camera and human motions without conflicts, human conditions should be re-rendered under new camera trajectories. Therefore, we propose the global 3D world guidance that places the human condition into the “environment”, i.e., aligning SMPL-X from W_{hum} to W_{env} as shown in Figure 5(b).

Multi-Modal Alignment. Fortunately, 2D human pose keypoints subtly bridge W_{hum} and W_{env} . Formally, we first estimate 17 human keypoints $\{\mathbf{k}_{2D}^i\}_{i=1}^{17} \in \mathbb{R}^{17 \times 2}$ from the reference view I_{img} by ViTPose++ [Xu et al. 2023]. Then, we unproject 2D keypoints into W_{env} to obtain 3D keypoints $\{\mathbf{k}_{env}^i\}_{i=1}^{17} \in \mathbb{R}^{17 \times 3}$ through metric monocular depth \hat{D}_{img} and the intrinsic camera of the reference image. For SMPL-X in W_{hum} , the COCO17 regressor [Shen et al. 2024] is utilized to project the first frame’s SMPL-X character into $\{\mathbf{k}_{hum}^i\}_{i=1}^{17}$ corresponding to the same human keypoints. Consequently, a least-squares estimation [Umeyama 1991] based rigid transformation can be used to align \mathbf{k}_{hum} to \mathbf{k}_{env} as follows:

$$\min_{\tilde{s}, \tilde{R}, \tilde{t}} \sum_{i=1}^{17} w_i \|(\tilde{s}\tilde{R}(\mathbf{k}_{hum}^i)^T + \tilde{t})^T - \mathbf{k}_{env}^i\|^2, \quad (4)$$

where $\tilde{s}, \tilde{R}, \tilde{t}$ indicate the optimized scaling factor, rotation matrix, and translation vector, respectively. w_i denotes the confidence weight of 2D keypoint \mathbf{k}_{2D}^i . We discard any keypoints with confidence below 0.7, as they typically degrade alignment quality. Once the transformation parameters $\tilde{s}, \tilde{R}, \tilde{t}$ are determined, we apply them to all other

SMPL-X sequences under the assumption that they share the same rigid transformation. However, even minor orientation errors can accumulate, leading to physically unrealistic motion trajectories, such as ascending into the sky or descending into the ground. To address this, we adopt GeoCalib [Veicht et al. 2024] to estimate the gravity direction in W_{env} , which is then employed to calibrate the SMPL-X to ensure parallel gravity directions, as illustrated in Figure 5(b). For the alignment of Hamer [Pavlakos et al. 2024], which shares common vertices with the hand parts of SMPL-X, Hamer can also be aligned to W_{env} through the rigid transformation (Equation (4)). Additionally, we address the issue of hand occlusion for Hamer by masking occluded hand parts based on the rendered depth from SMPL-X. After the alignments of SMPL-X and Hamer sequences, we place all conditions into W_{env} , establishing the global 3D world guidance that allows for rendering concurrently controlled conditions under arbitrary camera trajectories and human motions as shown in Figure 5(c). Finally, these re-rendered conditions are sent to PCDController and RealisDance-DiT for generated outcomes, as shown in Figure 2.

5 Experiments

5.1 Implementation Details

PCDController is trained with the frozen Wan-I2V [Wang et al. 2025a] on multi-resolution images scaled from $[480 \times 768, 512 \times 720, 608 \times 608, 720 \times 512, 768 \times 480]$ of 81 frames. The learning rate is warmed up to 1e-5 for 400 steps and then fixed. We train the model for 6,000 steps with batch size 32, while more training steps would slightly hurt Wan-I2V’s generalization. The training is accomplished with 64 H100 GPUs for 40 hours. We also provided results based on CogVideoX-5B-I2V [Yang et al. 2025], training for 20k steps with batch size 16. During the training, we randomly drop 10% texts, as well as 5% point cloud renderings and Plücker embeddings. For inference, we set the classifier-free guidance scale to 5.0 for textual conditions, keeping other guidance on the default scale 1.

Datasets. To ensure the generalization of PCDController, we collect large-scale training data for camera control, including DL3DV [Ling et al. 2024], RE10K [Zhou et al. 2018], ACID [Liu et al. 2021], Co3Dv2 [Reizenstein et al. 2021], Tartainair [Wang et al. 2020],

Map-Free-Reloc [Arnold et al. 2022], WildRGBD [Xia et al. 2024], COP3D [Sinha et al. 2023], UCCo3D [Liu et al. 2025]. This comprehensive dataset encompasses various scenarios, featuring static and dynamic scenes, as well as object-level and scene-level environments. Furthermore, all datasets are annotated with metric-aligned monocular depth through the way proposed in [Cao et al. 2025] or are provided with ground-truth depth.

5.2 Results of Camera Control

Benchmark. To evaluate camera control ability, we built an out-of-distribution benchmark with 32 images across various domains, including text-to-image generation¹, real-world [Barron et al. 2022; Knapsch et al. 2017], object-centric, and human scenes as in Figure 17. Each image has four distinct camera trajectories, resulting in 128 test samples. Moreover, we collect a larger benchmark of 500 samples, comprising 50 scene images from megascenes [Tung et al. 2024] and 50 human scenes collected from the Internet. For each image, 5 random trajectories are assigned. We used VBench++ [Huang et al. 2024] to evaluate the video quality, while absolute translation error (ATE), relative translation error (RPE), and relative rotation error (RRE) are used to verify the camera precision. We utilize VGGT [Wang et al. 2025b] to produce extrinsic cameras for the generated images, which are then evaluated against the predefined cameras after trajectory alignment.

Analysis. We present the quantitative results in Table 1, comparing our model with ViewCrafter [Yu et al. 2024], SEVA [Zhou et al. 2025a], and the CogVideoX [Yang et al. 2025] version of our framework. The qualitative outcomes are shown in Figure 7. Our experiments demonstrate that point clouds significantly enhance the controllability of both the Wan2.1 and CogVideoX, as verified by the improvement of ATE, RPE, and RRE. Although SEVA achieves precise camera trajectories, it requires massive training with static multi-view data (0.8M iterations), struggling to handle dynamic out-of-distribution scenarios, such as humans and animals, as illustrated in Figure 7. We should clarify that our baseline, Wan-I2V with only Plücker ray, suffers from inferior camera movements. While this setting achieves a strong VBench overall score, it compromises with poor camera metrics. Overall, the proposed PCDController achieves the optimal balance between video quality and camera precision. By integrating both Plücker rays and point clouds, it further enhances the performance in challenging scenes featuring substantial viewpoint changes, as validated in Table 1 and Figure 8. Furthermore, our method also performs well in the large benchmark on megascene and Internet human images as listed in Table 2.

5.3 Results of Unified Camera and Human Motion Control

Benchmark. We have developed a new benchmark of 50 videos of 720p, each featuring a person performing challenging motions. For guidance, SMPL-X is extracted using GVHMR [Shen et al. 2024]. Each video is assigned three different types of camera trajectories, resulting in a total of 150 test cases. To ensure that the person remains within the camera’s viewpoint, we employ a follow shooting technique for all test cases, adjusting the camera’s position based

on the movement of the SMPL-X center. These noisy and subtle movements further increase the difficulty of camera control. We follow the same camera metrics as mentioned in Section 5.2. To facilitate generalization for motion transfer, RealisDance-DiT is not specifically designed to perfectly recover the first frame aligned with the reference image. Consequently, we remove the metrics that heavily depend on the reference view (I2V subject and background) in Table 3 for fairness. Note that our method performs well in 720p generation, even though it was trained using 480p data.

Analysis. We show quantitative results in Table 3, while qualitative results are displayed in Figure 6 and Figure 9. To our knowledge, there are currently very few available models that effectively address the challenge of unified camera and human motion controls. We begin by comparing to CamAnimate [Wang et al. 2024a], which enables simultaneous control of both conditions. However, due to the misalignment of body poses extracted relative to predefined camera trajectories, the results of CamAnimate suffer from conflicting human motions and backgrounds. Moreover, we evaluate Uni3C against the baseline of RealisDance-DiT [Zhou et al. 2025b] and various ablation versions of our model. Notably, while RealisDance-DiT, which focuses solely on human control, achieves the best visual quality, it struggles to produce accurate camera trajectories, resulting in poor camera metrics. In contrast, Uni3C shows good VBench scores alongside impressive camera metrics. Note that the proposed PCDController can also be generalized to the T2V model with comparable quality, featuring the robust generalization of PCDController. Moreover, an interesting insight is revealed from Figure 9 and Table 3 that the aligned SMPL-X characters can further strengthen the camera controllability, while the PCDController trained with I2V formulation also enhances the visual quality and consistency of RealisDance-DiT. This illustrates the complementary features of these two components. Additionally, we show that the proposed Uni3C enables control of detailed hand motions under various camera trajectories as in Figure 10.

5.4 Ablation Study and Exploratory Discussions

Plücker Ray vs Point Clouds. As shown in Table 1, point clouds enjoy significantly more precise camera trajectories. We further clarify that video camera control trained with point clouds achieves much faster convergence with lower training loss, as illustrated in Figure 13. Only 1,000 training iterations can hold the general camera trajectory. We empirically find that timing large-scale VDM like Wan-I2V through Plücker ray is difficult. Maybe enabling more trainable parameters would improve the performance, potentially hindering the generalization, which is not considered in this work. Moreover, as verified in the last two rows of Table 1, using both Plücker ray and point clouds improves the results of very challenging camera trajectories.

Point Clouds of Humans. Human point clouds are always frozen in world space without any motion, which conflicts with the human motion conditions provided by SMPL-X. Eliminating this “redundant” information is a straightforward idea to improve motion quality. However, as verified in Table 3, while Uni3C-T2V with human-masked point clouds achieves slightly better visual quality,

¹<https://github.com/black-forest-labs/flux>

Table 1. **Quantitative results of camera control.** VBench++ scores (%) are normalized (higher is better). Injected camera features are divided as Plücker ray and point clouds (Pcd). † denotes the results with challenging 360° camera rotations. Results of MotionCtrl and CameraCtrl are tested with the I2V version re-trained by [Zheng et al. 2025a]. Methods in **bold** are the final setting of PCDController.

| | Camera Plücker Pcd | Overall Score | Subject Consist | Bg Consist | Aesthetic Quality | Imaging Quality | Temporal Flicker | Motion Smooth | I2V Subject | I2V Bg | ATE↓ | RPE↓ | RRE↓ |
|--------------------------------|--------------------------|------------------|--------------------|---------------|----------------------|--------------------|---------------------|------------------|----------------|-----------|-------|-------|-------|
| MotionCtrl [Wang et al. 2024b] | | 82.48 | 89.42 | 91.64 | 54.99 | 55.02 | 91.93 | 95.85 | 89.92 | 91.11 | 0.345 | 0.263 | 2.547 |
| CameraCtrl [He et al. 2025a] | ✓ | 83.69 | 90.17 | 92.21 | 55.71 | 54.13 | 93.32 | 96.65 | 93.34 | 94.01 | 0.354 | 0.239 | 2.306 |
| CamI2V [Zheng et al. 2025a] | ✓ | 86.52 | 91.45 | 92.65 | 60.91 | 66.22 | 93.34 | 97.01 | 95.17 | 95.45 | 0.322 | 0.247 | 1.653 |
| ViewCrafter [Yu et al. 2024] | ✓ | 85.39 | 89.69 | 91.68 | 55.13 | 64.33 | 92.94 | 97.66 | 95.59 | 96.11 | 0.210 | 0.117 | 0.873 |
| SEVA [Zhou et al. 2025a] | ✓ | 87.39 | 91.86 | 93.36 | 56.79 | 68.43 | 95.74 | 98.59 | 97.08 | 97.23 | 0.077 | 0.029 | 0.223 |
| Ours (CogVideoX) | ✓ | 86.48 | 93.17 | 93.02 | 55.00 | 66.75 | 95.10 | 98.36 | 94.45 | 95.94 | 0.356 | 0.162 | 1.280 |
| Ours (CogVideoX) | ✓ | 87.22 | 91.26 | 92.44 | 56.90 | 69.53 | 94.79 | 98.47 | 96.60 | 97.79 | 0.123 | 0.045 | 0.346 |
| Ours (Wan-I2V) | ✓ | 89.16 | 94.71 | 94.93 | 60.42 | 72.20 | 96.51 | 98.51 | 97.74 | 98.29 | 0.402 | 0.095 | 0.728 |
| Ours (Wan-I2V) | ✓ | 87.95 | 91.71 | 92.97 | 58.52 | 71.12 | 95.51 | 98.55 | 97.24 | 97.96 | 0.091 | 0.028 | 0.211 |
| Ours (Wan-I2V) | ✓ | 88.27 | 92.20 | 93.37 | 58.99 | 71.96 | 95.56 | 98.66 | 97.38 | 98.01 | 0.102 | 0.031 | 0.246 |
| Ours (Wan-I2V)† | ✓ | 82.70 | 82.16 | 88.72 | 53.67 | 66.95 | 91.41 | 95.45 | 90.80 | 92.47 | 1.327 | 0.551 | 6.334 |
| Ours (Wan-I2V)† | ✓ | 82.82 | 82.31 | 88.75 | 53.56 | 66.25 | 90.81 | 95.23 | 92.12 | 93.49 | 1.010 | 0.416 | 4.428 |



Fig. 6. **Results of unified camera and human motion controls.** Leftmost images are reference views; the first row indicates aligned 3D world guidance.

Table 2. **Camera control results on large benchmark with 500 samples** collected from megascenes [Tung et al. 2024] and Internet human scenes. ‘Overall’ means the average score across all metrics of VBench++.

| | Overall↑ | ATE↓ | RPE↓ | RRE↓ |
|------------------------------|--------------|---------------|---------------|---------------|
| CamI2V [Zheng et al. 2025a] | 83.62 | 0.8081 | 0.6858 | 2.5803 |
| ViewCrafter [Yu et al. 2024] | 84.26 | 0.6224 | 0.4098 | 1.2642 |
| SEVA [Zhou et al. 2025a] | <u>84.83</u> | 0.2473 | <u>0.0832</u> | <u>0.5329</u> |
| PCDController | 86.62 | <u>0.2613</u> | 0.0828 | 0.4612 |

this masking adversely affects camera precision, particularly when humans occupy a significant image area. Therefore, retaining the point clouds of humans is essential for effective camera control. Given that Wan.2.1 [Wang et al. 2025a] is trained on videos featuring substantial motion, it can generate natural and smooth movements even when the foreground point clouds remain fixed.

Gravity Calibration. As mentioned in Section 4.3, gravity calibration is critical for aligning the global 3D world space. Results shown in Figure 14 verify that the calibration can correct the SMPL-X characters aligned with skewed human point clouds and eliminate the error accumulation for humans’ long-distance movements.

Motion Transfer. We present motion transfer results achieved by the Uni3C framework in Figure 11. Our model effectively controls both camera trajectories and human motions, even when reference motions are sourced from different videos or distinct domains,

such as animation and real-world scenes. Meanwhile, Uni3C can be further extended to generate vivid videos based on other conditions, like text-to-motion guidance or retrieved motions from motion databases. To prove this point, we randomly integrate several motion clips generated text-to-motion [Barquero et al. 2024] trained on BABEL [Punnakkal et al. 2021] and use Uni3C to control both motion and camera, as illustrated in Figure 12. More results are shown in our supplementary.

Ablation of PCDController. We present some ablation results of PCDController with various external DiT layers in Table 4. Each setting injects conditional features into the main Wan-I2V backbone from top to bottom with different layers. While the DiT branch with 30 layers shows slightly improved camera metrics, it ultimately compromises overall visual quality and generalization. We reveal that solely applying more external layers suffers from overfitting point cloud conditions as shown in Figure 15, resulting in suboptimal outcomes with distorted point clouds. Thus, we determine that employing 20 DiT layers achieves an effective balance between controllability and generalization within the PCDController.

5.5 User Study

We conducted user studies for camera control (128 samples) and unified control (150 samples) on our respective benchmarks in Table 5. Formally, 20 unrelated volunteers are invited. For the camera

Table 3. **Quantitative results of unified camera and human motion controls.** “Aligned” control means re-rendering human conditions under new camera trajectories in the environmental world space. † denotes masking out the foreground point clouds of humans. Method in **bold** is the final setting of Uni3C.

| | Control | | | Overall | Subject | Bg | Aesthetic | Imaging | Temporal | Motion | |
|-------------------------------------|---------|-------|---------|---------|---------|---------|-----------|---------|----------|--------|-------------------|
| | Camera | Human | Aligned | Score | Consist | Consist | Quality | Quality | Flicker | Smooth | ATE↓ RPE↓ RRE↓ |
| CamAnimate [Wang et al. 2024a] | ✓ | ✓ | | 82.45 | 89.20 | 90.52 | 57.42 | 67.40 | 93.94 | 96.20 | 0.619 0.419 2.035 |
| RealisDance-DiT [Zhou et al. 2025b] | | ✓ | ✓ | 85.21 | 93.03 | 95.34 | 57.89 | 68.71 | 97.44 | 98.82 | 0.549 0.195 0.547 |
| PCDController | ✓ | | | 83.19 | 89.08 | 91.63 | 57.23 | 68.27 | 95.22 | 97.71 | 0.256 0.092 0.661 |
| Uni3C (T2V)† | ✓ | ✓ | ✓ | 83.34 | 88.45 | 91.45 | 57.45 | 69.84 | 95.21 | 97.63 | 0.296 0.098 1.167 |
| Uni3C (T2V) | ✓ | ✓ | ✓ | 83.16 | 88.67 | 91.38 | 56.79 | 69.42 | 95.14 | 97.57 | 0.262 0.083 0.606 |
| Uni3C (I2V, unaligned) | ✓ | ✓ | | 82.98 | 89.16 | 92.40 | 56.02 | 66.78 | 95.65 | 97.84 | 0.270 0.111 0.639 |
| Uni3C (I2V) | ✓ | ✓ | ✓ | 83.43 | 89.45 | 93.05 | 57.25 | 67.28 | 95.70 | 97.86 | 0.251 0.093 0.490 |

Table 4. **Ablation of PCDController.** Different DiT layers are employed from top to bottom. PCDController adopts **20-layer** as the final setting.

| External DiT Layer | Overall Score | ATE↓ | RPE↓ | RRE↓ |
|--------------------|---------------|--------------|--------------|---------------|
| 10 | 0.48B | 87.75 | 0.136 | 0.0398 |
| 20 | 0.95B | 88.27 | 0.102 | 0.0313 |
| 30 | 1.39B | 88.08 | 0.092 | 0.0302 |
| 40 | 1.85B | 87.90 | 0.115 | 0.0339 |
| | | | | 0.216 |

Table 5. **User studies on camera and unified (camera&human) control.**

| Camera | Cam2V | ViewCrafter | SEVA | PCDController |
|------------------|------------|-----------------|---------------|---------------|
| VideoQuality↑ | 0.0391 | 0.0855 | 0.2328 | 0.6457 |
| CameraPrecision↑ | 0.0359 | 0.1003 | 0.2429 | 0.6281 |
| Camera&Human | CamAnimate | RealisDance-DiT | PCDController | Uni3C |
| VideoQuality↑ | 0.0170 | 0.2466 | 0.0453 | 0.6920 |
| CameraPrecision↑ | 0.0676 | 0.2766 | 0.5266 | 0.8976 |
| HumanPose↑ | 0.0716 | 0.5863 | 0.1730 | 0.8983 |

control, volunteers are requested to vote for the best result, considering video quality and camera precision, while the quality of human pose is additionally required for the unified control. If two methods perform very similarly, volunteers are allowed to vote for both of them as top-2. We finally average the score for each metric.

6 Limitation and Future Work

Although Uni3C supports flexible and diverse unified control and motion transfer, it operates under the constraints of predefined camera trajectories and human characters (SMPL-X). Consequently, Uni3C struggles to produce physically plausible outcomes when human motions conflict with environmental conditions, as shown in Figure 16. For instance, if a human’s movement trajectory is blocked by walls, barriers, or other objects, the generated results may exhibit artifacts such as distortion, clipping, or sudden disappearance. This limitation could be mitigated by employing a more advanced human motion generation method that accounts for physical obstructions within the environment. Besides, though our method can produce plausible results within inaccurate SMPL or world coordinates, it will result in undesired pose or motion direction.

7 Conclusion

This paper introduced Uni3C, a framework that unifies 3D-enhanced camera and human motion controls for video generation. We first propose the PCDController, demonstrating that lightweight, trainable modules, and rich geometric priors from 3D point clouds can

efficiently manage camera trajectories without compromising the inherent capacities of foundational VDMs. This not only enhances generalization but also facilitates versatile downstream applications without joint training. Furthermore, by aligning multi-modal conditions, including both environmental point clouds and human characters in a global 3D world space, we established a coherent framework for jointly controlling camera movements and human animations. Our comprehensive experiments validated the efficacy of Uni3C across diverse datasets, showcasing superior performance in both quantitative and qualitative assessments compared to existing approaches. The significance of our contributions lies not only in improving the state-of-the-art in controllable video generation but also in proposing a robust way to inject multi-modal conditions without the requirements of heavily annotated data. We believe that Uni3C paves the way for advanced controllable video generation.

Acknowledgments

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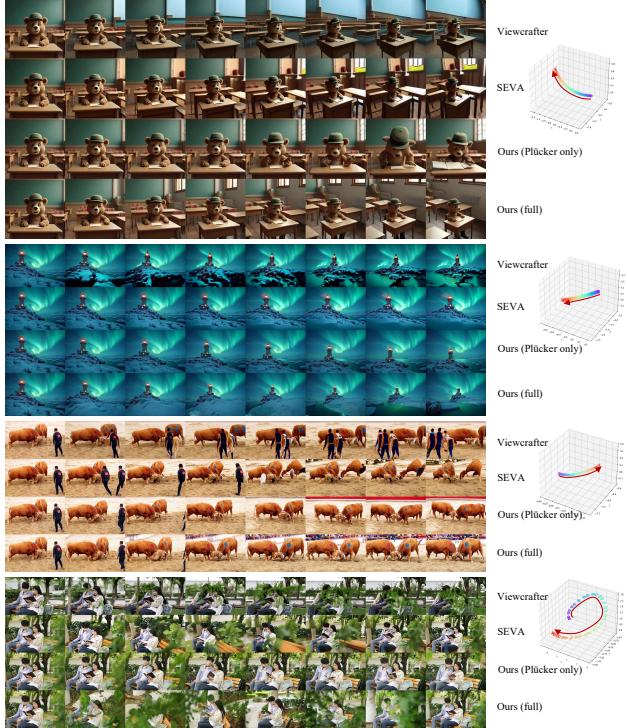


Fig. 7. Qualitative results of camera control on our benchmark. We compare the proposed PCDController to ViewCrafter [Yu et al. 2024], SEVA [Zhou et al. 2025a], and our model without point cloud guidance. The leftmost image is the reference condition. “full” indicates using both Plücker ray and point clouds as conditions.

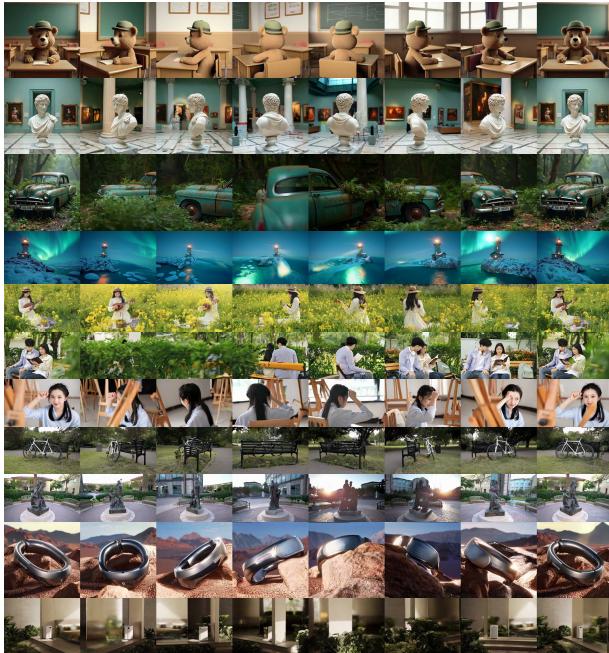


Fig. 8. Results of the challenging orbital 360° rotations from PCD-Controller. The leftmost images are the reference views.

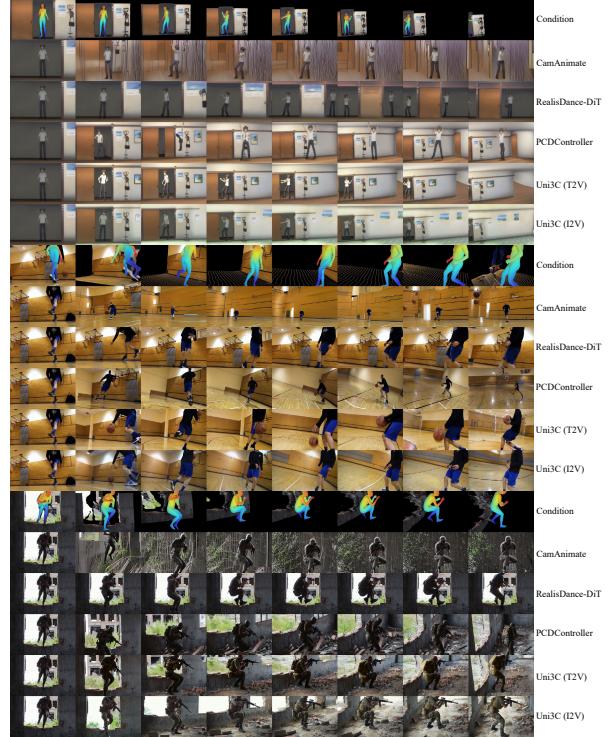


Fig. 9. More results of unified camera and human motion controls. Leftmost images are reference views; the first row indicates aligned 3D world guidance.

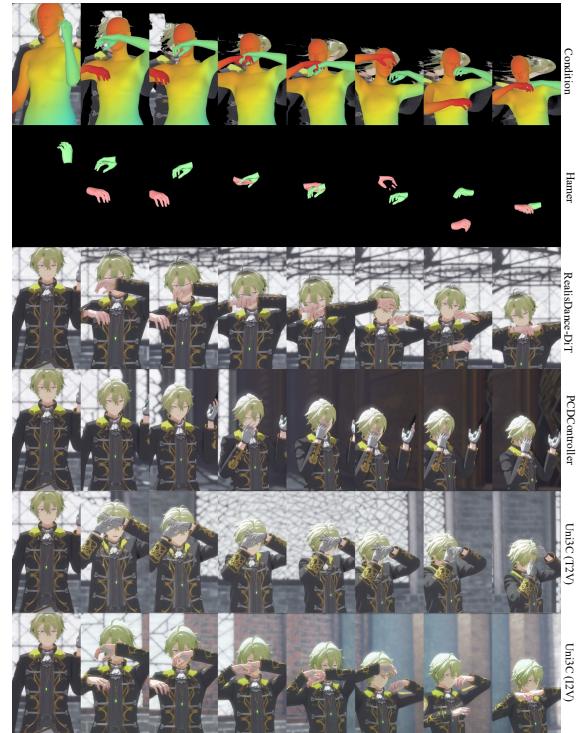


Fig. 10. Results of unified camera, human motion, and Hamer controls. The leftmost images are the reference views, while the first and second rows indicate the aligned 3D world guidance and Hamer rendering.

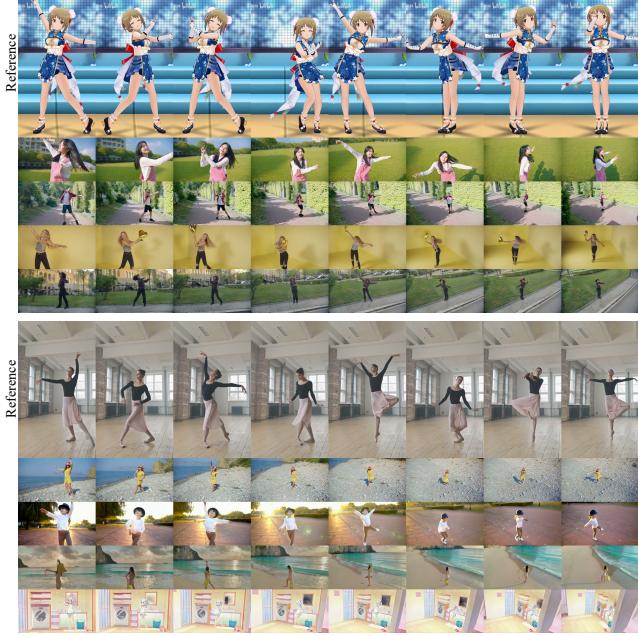


Fig. 11. Results of motion transfer. The first row indicates the reference video, while others show our generated videos transferring motions from the reference sequence.

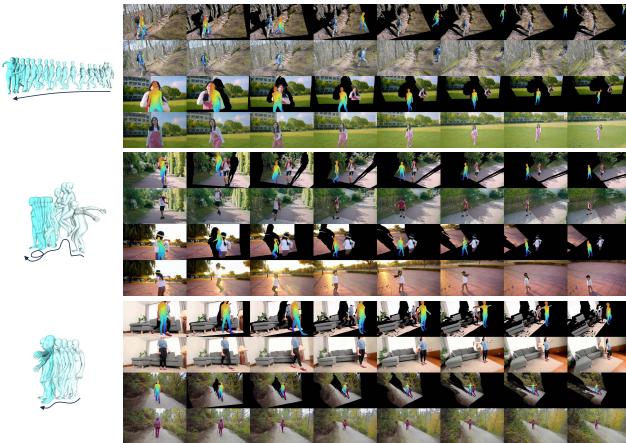


Fig. 12. Results transferred from randomly integrated motion clips generated from text-to-motion [Barquier et al. 2024] trained on BABEL [Punnakkal et al. 2021]. The motion sequences are listed on the left, which are executed from light to dark colors.

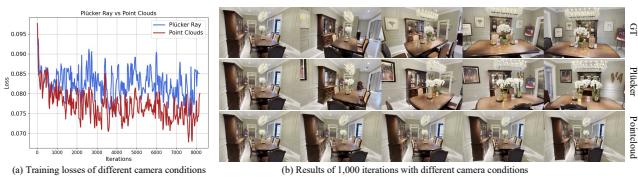


Fig. 13. Ablation results of Plücker ray and point clouds during training phase. Point clouds enjoy highly accurate camera control against Plücker ray.



Fig. 14. Rendering results with and without gravity calibration by GeoCalib [Veicht et al. 2024].



Fig. 15. Camera control results of PCDController with challenging point clouds. The model with fewer external DiT layers enjoys superior conditional robustness compared to the one with more DiT layers.



Fig. 16. Failed cases generated by Uni3C. These results are primarily limited by the conflict between human motions and environments.



Fig. 17. Our out-of-distribution benchmark for camera control. The validation set includes generative, human, scene-level, and object-level images with diverse aspect ratios.

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A Border Impact

This study delves into the realm of controllable video generation. The remarkable generative capabilities of AI-generated content (AIGC) can inadvertently lead to the creation of misleading information or fabricated visuals. Consequently, we sincerely urge users to remain vigilant regarding these issues. Moreover, issues of privacy and consent must be taken into account, as generative models are always developed using extensive datasets. It's also crucial to acknowledge that such models can potentially reinforce biases in the training data, which may result in unjust outcomes. Therefore, we advise users to be responsible and inclusive when utilizing these generative models. It is important to mention that our method concentrates solely on technical aspects. All pre-trained models and training videos referenced in this study are publicly available.

B Details of Uni3C

B.1 Architecture Details of PCDController

As mentioned in the main paper, our PCDController is built upon a simplified DiT module. We apply detailed ablation studies and demonstrate that the 20-layer external DiT branch with 1024 hidden size enjoys a good balance between both controllability and generalization. Detailed architecture of PCDController is illustrated in Figure 18. We follow the DiT design in CogVideoX [Yang et al. 2025], including AdaLayerNorm, 3D attention, and Feed Forward Network (FFN), without the textual branch. The output features are added to the main branch of Wan-I2V block by block via zero-initialized projection layers.

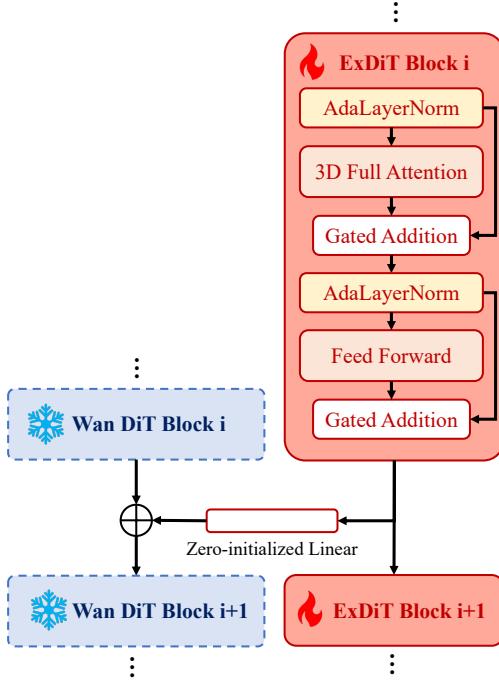


Fig. 18. Detailed model architecture of PCDController.

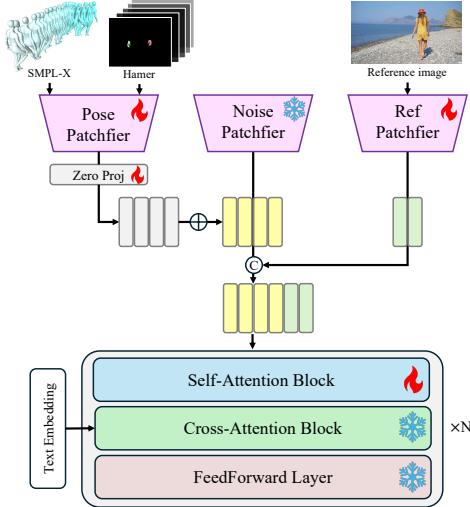


Fig. 19. Detailed architecture of Realisdance-DiT [Zhou et al. 2025b].

B.2 Architecture Details of Realisdance-DiT

We show the model architecture of Realisdance-DiT [Zhou et al. 2025b] in Figure 19 employed for our unified controls for both camera and human poses. Formally, Realisdance-DiT is fine-tuned from the pre-trained Wan-I2V, while features of human condition signals (SMPL-X and Hamer) are added to the inputs, and the reference image feature is spatially concatenated to the inputs to confirm fine-grained details. During the training of Realisdance-DiT, only convolution-based pose and reference patchfiers and self-attention layers of DiT are trainable.

Table 6. Inference efficiency of Uni3C. Our model only increases a little inference time compared to the baseline method.

| Methods | Inference Times | |
|-----------------|-----------------|---------------|
| | 480×768 | 720×1280 |
| RealisDance-DiT | 50.5s | 182.7s |
| Uni3C | 62.3s (+23%) | 213.4s (+17%) |

Table 7. Efficiency of other components of Uni3C.

| PyTorch3D-Rendering | 2D-Keypoint+Alignment | GeoCalib |
|---------------------|-----------------------|----------|
| 4.341s | 0.577s | 1.459s |

B.3 High-Resolution Inference

While PCDController is trained under 480p multi-view images (480×768, 512×720, 608×608, 720×512, 768×480), we find that this model also performs well under 720p video generation (720×1280, 800×1152, 960×960, 1152×800, 1280×720) without specific fine-tuning, as empirically verified in our qualitative results in the supplementary. Specifically, for the inference of 720p, we first render the conditional videos of warped point clouds with PyTorch3D under 480p. Then we replace the first frame with a 720p reference image as the high-resolution guidance. Thus, PCDController can produce high-quality 720p videos extended from the high-resolution reference, while the low-resolution point cloud renderings are only considered as auxiliary camera signals.

B.4 Inference Efficiency

We evaluate the inference efficiency of Uni3C in comparison to the baseline model, RealisDance-DiT [Zhou et al. 2025b], across two different resolutions, as detailed in Table 6. Note that the efficiency of RealisDance-DiT [Zhou et al. 2025b] is almost the same as the basic VDM, Wan-I2V [Wang et al. 2025a], while only a few convolution layers are newly incorporated to encode additional conditions. For this analysis, we utilize the official settings from Wan2.1 [Wang et al. 2025a], which include a 40-step denoising process and a classifier-free guidance scale of 5. The inference environment is configured using a sequence parallel based on 8 Nvidia H100 GPUs. We further provide other detailed time costs of Uni3C in Table 7. Overall, Uni3C demonstrates impressive efficiency in this setup.

C Details of Datasets

We summarized our training data setting in Table 8. A sampling strategy across epochs ensures balanced sample scales over different data domains. Formally, we pay more attention to the data with high-quality images and complex camera trajectories of real-world scenarios like DL3DV [Ling et al. 2024] and UCo3D [Liu et al. 2025].

D Inference Details of Camera Control

During the inference phase, we begin by extracting the monocular depth of the reference view using Depth-Pro [Bochkovskii et al. 2024]. We then establish the foreground depth medium, defined as the rotation radius, to determine the placement of the initial camera. For extracting the foreground mask, we utilize CarveKit². In cases

²<https://github.com/OPHoperHPO/image-background-remove-tool>



Fig. 20. **Results of Uni3C under the two-person scenario.** We operate two different camera trajectories, while their human motions follow the input video.

Table 8. Dataset details of training PCDController. The training datasets include Co3Dv2 [Reizenstein et al. 2021], DL3DV [Ling et al. 2024], RE10K [Zhou et al. 2018], ACID [Liu et al. 2021], Tartainair [Wang et al. 2020], Map-Free-Reloc [Arnold et al. 2022], WildRGBD [Xia et al. 2024], COP3D [Sinha et al. 2023], and UCo3D [Liu et al. 2025]. We dynamically sample subsets for each dataset across training epochs.

| | Indoor | Outdoor | Object | Synthetic | Scene Number | | |
|----------------|--------|---------|--------|-----------|--------------|------------|--------|
| | | | | | Train | Validation | Epoch |
| Co3Dv2 | ✓ | ✓ | ✓ | | 24,437 | 53 | 2,252 |
| DL3DV | ✓ | ✓ | | | 9,808 | 250 | 19,868 |
| RE10K | ✓ | ✓ | | | 20,259 | 50 | 7,528 |
| ACID | | ✓ | | | 2,575 | 20 | 1,047 |
| Tartainair | ✓ | ✓ | | ✓ | 2,834 | 50 | 2,834 |
| Map-Free-Reloc | ✓ | ✓ | | | 892 | 18 | 1,784 |
| WildRGBD | ✓ | ✓ | ✓ | | 22,105 | 46 | 2,300 |
| COP3D | ✓ | ✓ | | | 2,109 | 20 | 2,109 |
| UCo3D | ✓ | ✓ | ✓ | | 161,591 | 99 | 10,000 |

where no foreground is detected, the entire image is treated as the foreground. Our camera control is based on two primitives:

- **Rotation.** We define the rotation along azimuth and elevation, respectively. The rotation radius is used to control the distance to the foreground, serving as the center of rotation.
- **Translation:** We implement translation along the x, y, and z axes. The translation values are constrained within the range

of [0, 1.0], which are then multiplied by the rotation radius to ensure that translations do not become excessively large or small.

Overall, the camera control mechanism proposed in this paper is flexible and effective enough to handle most downstream tasks.

E Multiple-Person Discussion

Uni3C builds upon RealisDance-DiT [Zhou et al. 2025b], which is explicitly tailored for single-person scenarios. Notably, we observe that RealisDance-DiT retains functionality even in two-person scenarios, as verified by the case presented in [Zhou et al. 2025b] and visualized in Figure 20. Formally, we separately align two persons’ SMPL-X representations, guided by their respective 3D keypoints. However, injecting additional control signals from more people would hinder the performance. This outcome is unsurprising, as multi-person control is significantly outside the scope of RealisDance-DiT training. As a plug-and-play module, Uni3C can be integrated with other backbones that are natively designed for addressing multi-person control in the future.