Interactive Panoramic World Exploration via Camera Control

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Fig. 1. Qualitative examples of videos generated by Wan360. Wan360 is a camera-controllable interactive panoramic video generation model towards world exploration. To show the ability of following camera pose, we annotate the trajectory of generated videos.

Interactive panoramic video generation aims to synthesize immersive 360° videos that remain visually coherent while following user-specified camera trajectories during exploration. However, progress is limited by a coupled data-and-model gap: existing panoramic video datasets are often short, weakly annotated, or lack camera trajectories, while existing camera-controlled video generation models are designed for perspective videos and do not directly support panoramic geometry. In this paper, we introduce **MUGEN** and **Wan360** to address these limitations. **MUGEN** is a large-scale real-world panoramic video dataset tailored to interactive 360°

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world exploration, comprising over 1,300 hours of at least 4K panoramic videos with rich semantic and geometric annotations. Built on MUGEN, we further present **Wan360**, a camera-controllable interactive panoramic video generation model. Panoramic videos are commonly represented by EquiRectangular Projection (ERP), which unfolds a spherical 360° view into a rectangular frame with cyclic longitude seams and pole distortions. To this end, Wan360 introduces three parameter-free ERP-aware components: periodic longitude RoPE for seam-consistent positional encoding, ERP-aware padding for reducing boundary artifacts, and random roll yaw for consistent learning. For camera control, Wan360 uses a panoramic Plücker embedding that represents camera motion with ERP rays rather than perspective pinhole rays. Experiments show that MUGEN serves as a data foundation for panoramic world exploration, and that Wan360 enables high-quality, temporally coherent, camera-controllable 360° video generation. Code and data for this paper are at https://github.com/AlayaLab/MUGEN.

CCS Concepts: • **Computing methodologies** → **Computer vision**.

Additional Key Words and Phrases: world exploration, panoramic video generation, panoramic video dataset

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1 Introduction

Panoramic videos provide complete 360° visual observations of real-world environments, making them a natural medium for immersive world exploration in virtual reality, simulation, and embodied AI [Anderson et al. 2018; Chiariotti 2021; Yin et al. 2025]. For such exploration to be truly interactive, a generative system must satisfy three requirements simultaneously: it should synthesize high-fidelity panoramic content, maintain temporal and spherical consistency over time, and follow user-specified camera trajectories during generation. Recent advances in panoramic video generation have improved the visual quality of 360° videos [Fang et al. 2025; Liu et al. 2025; Tan et al. 2024; Wang et al. 2024; Xia et al. 2025; Xie et al. 2025; Yin et al. 2025], but interactive panoramic world exploration remains underdeveloped because both the data and the model architectures are still insufficient for controllable generation in dynamic real-world scenes.

From the data perspective, existing panoramic video datasets are not designed for world exploration. Generation-oriented datasets [Wang et al. 2024; Xia et al. 2025] mainly provide short captioned clips, which are useful for text-conditioned panoramic synthesis but do not provide explicit camera-trajectory annotations. Perception-oriented datasets [Huang et al. 2023; Xu et al. 2025; Yan et al. 2024; Zhang et al. 2025b] include masks, boxes, or tracking annotations, but they are typically limited in scale and duration and do not target camera control video generation. As a result, prior datasets rarely combine high-resolution real-world panoramic videos, minute-level temporal extent, semantic annotations, and geometric annotations such as camera trajectories. Lacking of such a dataset makes it difficult to train and evaluate models that can generate long, coherent, and controllable panoramic videos. To address this data gap, we introduce **MUGEN**, shown in Fig. 2, a large-scale real-world panoramic video dataset tailored to interactive 360° world exploration. MUGEN contains over 1,300 hours of high-fidelity panoramic videos at a resolution of at least 4K, with source videos longer than one minute and standardized one-minute clips for annotation and training. Each clip is paired with rich semantic annotations, including captions, scene categories, actions, weather, crowd density, and locations, as well as geometric annotations including camera trajectories, instance masks, and depth. To construct MUGEN, we design an automatic pipeline that collects panoramic videos from curated YouTube channels, performs format and content filtering, segments videos into minute-level clips, and annotates them using large multimodal models and geometry estimation tools. We further construct MUGEN-HQ, a 300-hour high-quality subset selected by quality and diversity, to support efficient model training and evaluation.

From the model perspective, directly extending existing video generation models to interactive panoramic generation is also non-trivial. Panoramic videos are usually represented in equirectangular projection (ERP), whose geometry differs fundamentally from ordinary perspective frames: longitude is periodic, the left and right image boundaries correspond to the same seam, and the top and bottom rows collapse near the poles. Treating ERP frames as standard rasters can therefore introduce seam artifacts, pole artifacts, and spherical inconsistencies. To address this model gap, we propose **Wan360**, a camera-controllable panoramic image-to-video model trained on MUGEN-HQ. Wan360 is fine-tuned from the perspective camera-control baseline Wan2.2-Fun-5B-Control-Camera [Wan et al. 2025] and adapts it to ERP panoramas through three parameter-free ERP-aware components. **Periodic longitude RoPE** enforces cyclic positional encoding along the horizontal longitude dimension, **ERP-aware padding** reduces seam artifacts in VAE encoding and decoding, and **random roll yaw** exposes the model to yaw-equivalent panoramic observations while preserving the corresponding camera trajectories. For camera control, Wan360 uses a panoramic Plücker embedding [Ji et al. 2025], replacing perspective pinhole rays with ERP rays to enable trajectory conditioning without conventional camera intrinsics. These components allow Wan360 to reuse the pretrained video generation baseline while avoiding additional trainable modules.

Experiments demonstrate the effectiveness of both MUGEN and Wan360. We evaluate the annotation quality of MUGEN and show that its semantic and geometric annotations provide reliable data support for interactive panoramic world exploration. We further compare Wan360 with existing panoramic video generation methods and conduct ablations on its ERP-aware components. The results show that Wan360 achieves strong panoramic video quality, temporal coherence, and camera-trajectory controllability, indicating that the improvements come from both the scale and quality of MUGEN and the proposed ERP-aware components.

To sum up, our contributions are as follows: (i) We propose **MUGEN**, a large-scale, long-duration, high-quality real-world panoramic video dataset for interactive panoramic world exploration, containing over 1,300 hours of videos with rich semantic and geometric annotations. (ii) We present **Wan360**, a camera-controllable panoramic video generation model that adapts to ERP geometry via three parameter-free ERP-aware components and a panoramic Plücker embedding. (iii) Extensive experiments validate

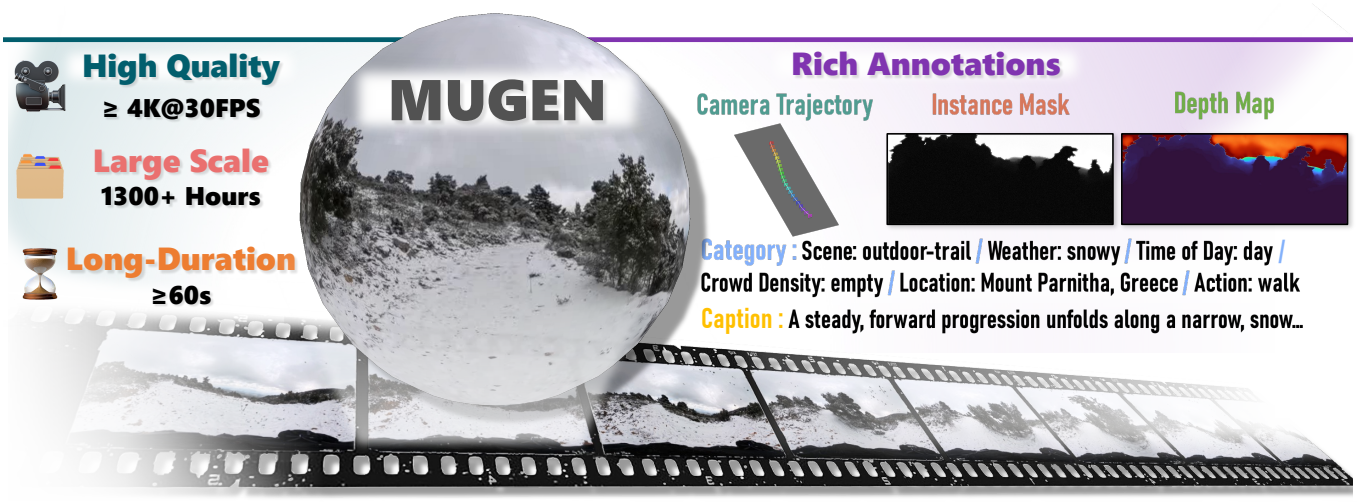


Fig. 2. MUGEN dataset overview. We introduce a large-scale panoramic video dataset featuring high-quality, long-duration 360° videos totaling 1,300+ hours at the resolution of at least 4K, paired with rich multi-level annotations including camera trajectories, instance masks, depth maps, natural language captions, and structured semantic labels.

the annotation quality of MUGEN and the generation quality of Wan360.

2 Related Work

2.1 Panoramic Video Datasets

Existing panoramic video datasets mainly support either generation or perception. Generation-oriented datasets such as WEB360 [Wang et al. 2024] and PANOVID [Xia et al. 2025] provide captioned panoramic clips for text-conditioned synthesis, but their annotations are primarily semantic and lack explicit camera trajectories. 360-1M [Wallingford et al. 2024] targets static novel view synthesis from frame pairs, PanFlow [Zhang et al. 2026] curates a motion-rich panoramic dataset with frame-level pose and flow annotations tailored to optical-flow-conditioned motion control, whereas MUGEN provides trajectories and richer annotations, better suiting panoramic world exploration. Perception-oriented datasets such as 360VOT/360VOTS [Huang et al. 2023; Xu et al. 2025], PanoVOS [Yan et al. 2024], and Leader360V [Zhang et al. 2025b] provide tracking or segmentation annotations, but are not designed for world exploration. In contrast, MUGEN is the first dataset with large-scale real-world 360° videos, minute-level duration, high visual fidelity, semantic labels, and geometric annotations including camera trajectories, depth, and instance masks to support interactive world exploration.

2.2 Panoramic Video Generation

Recent panoramic video generation methods adapt general video priors to ERP geometry using panorama-specific adapters [Wang et al. 2024], scalable generation [Liu et al. 2025], spherical or panorama-aware representations [Park et al. 2025; Xia et al. 2025; Xie et al. 2025; Zhang et al. 2025a], and perspective-to-panorama lifting [Fang et al. 2025; Li et al. 2026, 2024; Lu et al. 2025; Tan et al. 2024]. These works improve visual fidelity and scene coverage, but ERP panoramic video generation still requires geometry-aware mechanisms to handle longitude periodicity, boundary artifacts, and yaw-equivalent observations. Wan360 achieves higher-quality panoramic video generation through three parameter-free ERP-aware components that address these geometric properties. These components share related geometric intuitions with several prior works, but differ in how they are formulated and applied. PanoSplatt3R [Ren et al. 2025] approximates ERP periodicity through head-wise rolled linear RoPE coordinates. In contrast, our Periodic Longitude RoPE is exactly cyclic for every head, leading to better continuity at the seam. PAR [Wang et al. 2026] applies circular padding to panoramic image generation, whereas we extend it to the 3D video VAE for video generation. PanoDiffusion [Wu et al. 2023] rotates the panorama during training, our Random Roll Yaw also rotates the camera trajectory simultaneously, thereby enhancing the diversity of camera trajectories during training.

2.3 Camera-Controlled Video Generation

Camera-controlled video generation typically injects control signals into the model in two ways: by converting camera motion into Plücker embeddings [He et al. 2024a], or by adding explicit discrete control cues into the text prompts [Wan et al. 2025]. Existing methods mainly focus on conventional perspective video generation. Although PanoWorld-X [Yin et al. 2025], CamPVG [Ji et al. 2025], and OmniRoam [Liu et al. 2026] enable camera-controlled interactive panoramic video generation, these methods operate primarily in static or quasi-static environments. In contrast, Wan360 targets dynamic real-world panoramic world exploration, emphasizing controllable generation under natural, diverse, and unconstrained conditions.

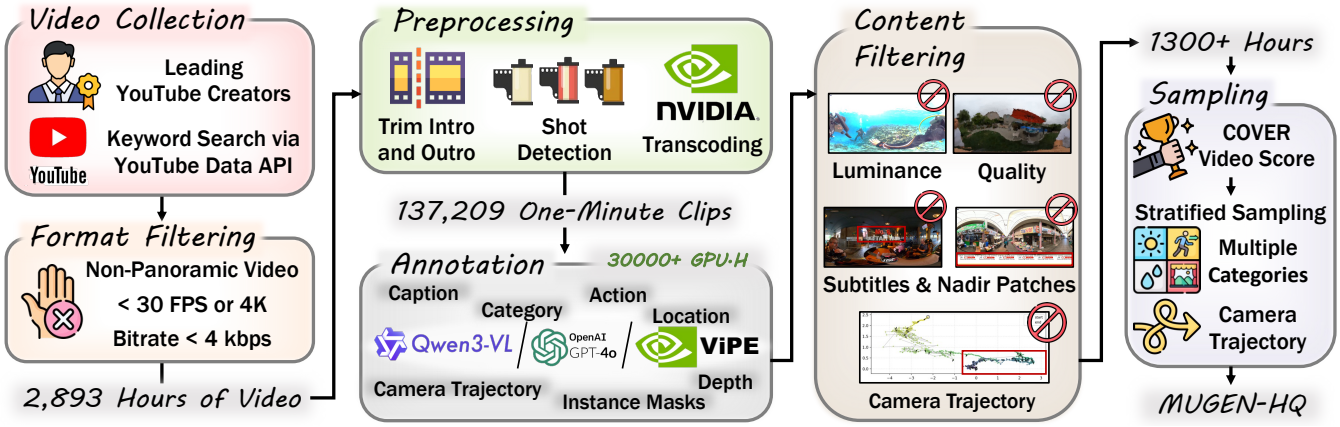


Fig. 3. Data curation pipeline for MUGEN. We collect 2,893 hours of panoramic source videos from YouTube, preprocess continuous footage into consecutive one-minute clips for scalable annotation, annotate each clip with semantic and geometric information using Qwen3-VL [Yang et al. 2025], GPT-4o [Hurst et al. 2024], and ViPE [Huang et al. 2025], filter clips by visual quality, overlays, and trajectory validity, and finally sample MUGEN-HQ for model training. The pipeline yields MUGEN (1,318 hours) and MUGEN-HQ (300 hours).

3 MUGEN Curation

To address the lack of large-scale, high-quality, richly annotated panoramic video datasets tailored to world exploration, we introduce MUGEN. Fig. 3 presents the data curation pipeline for our MUGEN dataset. We begin by collecting panoramic videos from YouTube, focusing on diverse real-world environments. To ensure high data fidelity, we apply strict format filtering based on resolution, bitrate, and frame rate. The filtered videos are then preprocessed into minute-level clips through intro/outro trimming, shot boundary detection, and standardized transcoding. Each clip is annotated with comprehensive semantic and geometric information using multi-modal models, followed by content-based quality filtering to produce the final MUGEN dataset. Furthermore, we construct MUGEN-HQ by sampling a high-quality subset with the most reliable and diverse annotations.

3.1 Data Acquisition and Preprocessing

We use YouTube as the primary source for diverse real-world panoramic videos. We manually curate leading panoramic video channels and search the YouTube Data API with queries such as "360 tour", then review the retrieved results to exclude non-real-world content such as simulation or rendered scenes. This stage yields 9,544 candidate source videos.

We further query video metadata and apply format filtering to retain high-fidelity panoramic videos. We remove non-panoramic videos and videos with frame rates below 30 FPS, resolutions below 4K, or bitrates below 4 kbps. For the remaining videos, we download the highest available resolution and best-quality audio, resulting in 2,893 hours of raw panoramic footage. All retained source videos are longer than one minute.

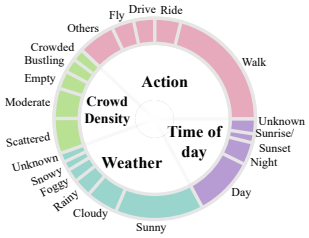
For preprocessing, we first verify file integrity and discard corrupted videos. We trim the first and last minute of each source video to remove common intro and outro segments. Because online videos are often edited, we use TransNetV2 [Souček and Lokoč 2020] to detect shot boundaries and keep only temporally continuous segments. Following Sekai [Li et al. 2025a], we accelerate shot-boundary processing with PyNvVideoCodec and CVCUDA. Each continuous segment is partitioned into consecutive non-overlapping 60-second clips, which makes large-scale annotation tractable and provides a consistent training unit. The clips are transcoded to H.265 at the original resolution and frame rate, with audio re-encoded to AAC at 48 kHz. This process produces 137,209 one-minute clips totaling approximately 2,287 hours before content filtering.

3.2 Annotation

MUGEN provides two groups of annotations: semantic annotations for content generation and geometric annotations for interactive camera control.

3.2.1 Semantic Annotations. Because ERP panoramas are difficult for vision-language models to parse directly, we project each ERP clip into six cube faces with a $90^\circ \times 90^\circ$ field of view and attach explicit face labels. We use Qwen3-VL-235B-A22B-Instruct [Yang et al. 2025] to generate detailed clip-level narratives of approximately 250 words, describing scene layout, visible objects, events, and camera motion. To support different training and evaluation settings, we also provide event-agnostic captions and interval captions at 5s/10s granularity. We further prompt Qwen3-VL with YouTube metadata to predict structured attributes, including weather, time of day, crowd density, scene category, and action. Following SpatialVID [Wang et al. 2025b], we refine coarse indoor/outdoor labels into fine-grained scene categories and introduce action labels tailored to world exploration. For geographic information, we use GPT-4o [Hurst et al. 2024] to extract location tags from video metadata; clips with ambiguous or missing locations are marked as *unspecified*.

3.2.2 Geometric Annotations. For camera-controllable generation, each clip requires trajectory annotations. We compare VGGT [Wang et al. 2025a], MegaSAM [Li et al. 2025b], and ViPE [Huang et al.



Statistic	Value
Translation	
Avg. Path Length	18.16 ± 14.74
Avg. Max Displacement	15.02 ± 13.42
Avg. Speed (unit/s)	0.30 ± 0.25
Rotation	
Avg. Total Rotation (°)	128.0 ± 192.3
Avg. Net Rotation (°)	30.6 ± 40.9
Avg. Angular Speed (°/s)	2.1 ± 3.2
Dominant Motion Direction	
Forward / Backward	44.3% / 17.3%
Left / Right	17.3% / 18.2%
Up / Down	0.5% / 0.4%
Static	2.1%

Fig. 4. Statistics of semantic attributes and camera trajectories in MUGEN. Left: semantic attribute distributions. Right: camera trajectory statistics.

2025] on sampled panoramic clips, and choose ViPE because it directly supports panoramic video input and produces more coherent camera trajectories in our setting. We use ViPE to estimate camera trajectories, instance masks, and depth for each clip. Generating geometric annotations for the full dataset requires over 30,000 GPU hours.

3.3 Quality Filtering

Raw web videos inevitably contain poor lighting, blur, overlays, stitching artifacts, or unreliable trajectories. We therefore apply four content filters before forming MUGEN.

3.3.1 Luminance. We compute the mean luma value of each clip and discard clips outside the range [40, 215] to remove underexposed or overexposed content.

3.3.2 Visual Quality. We score clips with COVER [He et al. 2024b] and remove clips below 0.7, which typically contain severe blur, distortion, or compression artifacts.

3.3.3 Overlays. We project each ERP clip into six perspective views and use Qwen3-VL [Yang et al. 2025] to flag subtitles, watermarks, and nadir patches.

3.3.4 Trajectory Validity. We filter clips whose estimated camera trajectories contain chaotic paths, temporal discontinuities, or abnormal rotations. After filtering, MUGEN contains 1,318 hours of high-quality one-minute clips from 6,446 unique source videos.

3.4 MUGEN-HQ Sampling

Although MUGEN is suitable for large-scale training and evaluation, model development often requires a smaller subset with high visual quality and balanced coverage. We therefore construct MUGEN-HQ, a 300-hour subset used for training Wan360. We first rank clips by COVER score and retain the top 70% as a quality-filtered pool. We then perform stratified sampling across scene categories, camera-motion patterns, action types, and weather conditions. This strategy preserves high visual quality while improving diversity in both scene content and controllable camera motion. MUGEN-HQ contains clips from 4,023 unique source videos.

3.5 Dataset Analysis

MUGEN covers diverse semantic and motion conditions for panoramic world exploration. As shown in Fig. 4, the dataset spans multiple weather types, times of day, crowd-density levels, scene categories, and action types. The trajectory statistics show substantial variation in translation length, rotation magnitude, angular speed, and dominant motion direction. These properties provide the semantic diversity and trajectory diversity needed to train and evaluate camera-controllable panoramic generation models. We will release metadata and processing scripts to support transparent reuse.

4 Wan360 Model

We present **Wan360**, a panoramic image-to-video (I2V) generation model that generates ERP videos from an input panorama, a text prompt, and a user-specified camera trajectory. Wan360 is fine-tuned from a perspective camera-control video generation baseline to preserve its strong generation and control priors, but this baseline cannot be directly applied to panoramas. ERP videos contain cyclic longitude seams and pole singularities, and panoramic cameras do not follow the perspective pinhole model. Naive fine-tuning would therefore introduce seam artifacts, spherical inconsistencies, and mismatched camera-control signals.

4.1 Component Overview

Figure 5 shows the overall architecture. Wan360 addresses the ERP geometry mismatch with three components that add no trainable parameters. *Periodic Longitude RoPE* (Section 4.2) makes longitude positional encoding seam-consistent, *ERP-Aware Padding* (Section 4.3) reduces boundary artifacts in VAE encoding and decoding, and *Random Roll Yaw* (Section 4.4) creates yaw-equivalent panorama-trajectory training pairs. For camera control, a *Panoramic Plücker Embedding* (Section 4.5) replaces the baseline's pinhole ray-condition generator with an ERP ray generator, enabling intrinsics-free trajectory conditioning.

4.2 Periodic Longitude RoPE

Perspective video baselines treat the horizontal image axis as a bounded coordinate, but ERP longitude is periodic: the left and right image boundaries represent adjacent directions on the sphere. Using the original positional encoding therefore introduces an artificial discontinuity at the panorama seam. Periodic Longitude RoPE replaces only the longitude part of the positional encoding with a cyclic formulation, while keeping the temporal and latitude parts unchanged for compatibility with the pretrained baseline. For a token at horizontal index u in a width-W latent grid, we map it to longitude

$$\theta_u = 2\pi \frac{u + 1/2}{W} - \pi, \qquad \rho_k(u) = \big(\cos(k\theta_u), \sin(k\theta_u)\big), \quad (1)$$

where k denotes the RoPE frequency. Because $\rho_k(u + W) = \rho_k(u)$, the positional code is continuous across the ERP seam. This makes tokens near the two horizontal boundaries geometrically consistent and reduces seam-related artifacts during fine-tuning.

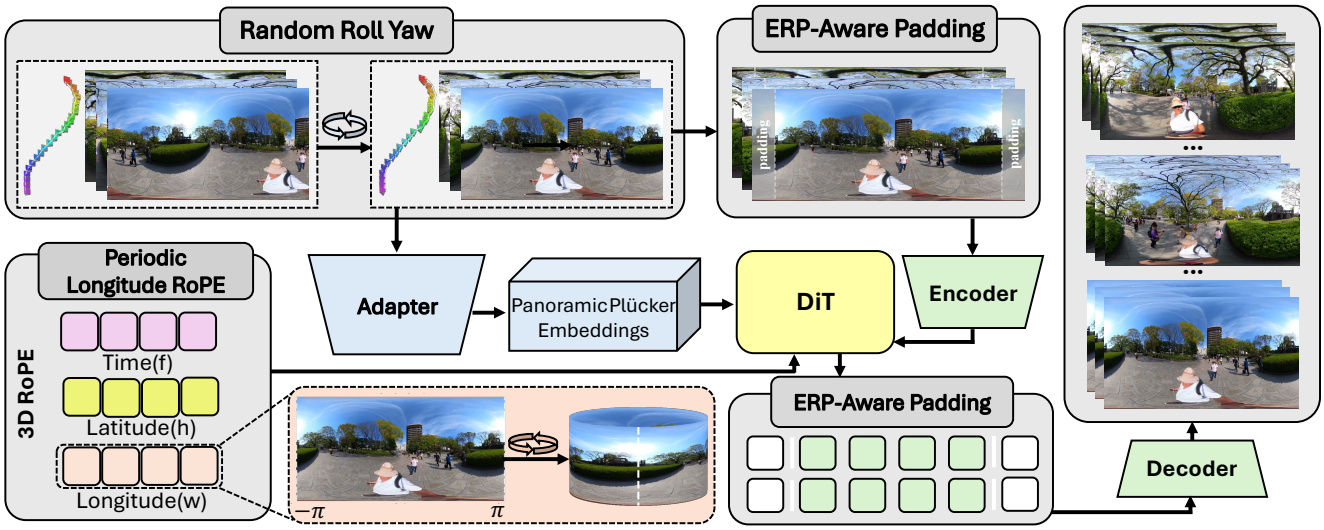


Fig. 5. Architecture of Wan360. Wan360 is a camera-controllable interactive panoramic video generation model towards world exploration conditioned on an input panorama, a text prompt, and a target camera trajectory. To adapt the perspective baseline to panoramic geometry, Wan360 introduces three parameter-free ERP-aware components: periodic longitude RoPE for cyclic longitude encoding, ERP-aware padding for seam-continuous VAE features, and random roll yaw for yaw-equivalent trajectory augmentation. A panoramic Plücker embedding converts ERP pixels into spherical rays and injects trajectory conditions through the pretrained control adapter.

4.3 ERP-Aware Padding

The VAE in the baseline uses local convolutions, whose default boundary handling assumes that image edges have no continuation. For ERP panoramas this assumption is incorrect, because pixels at the two horizontal borders are neighbors on the sphere. ERP-Aware Padding exposes this cross-boundary neighborhood by using longitude-cyclic padding during VAE encoding and decoding. For any VAE feature map z, horizontal padding is defined as

$$\tilde{z}_{t,v,u} = z_{t,v,u \bmod W}, \tag{2}$$

so convolutional neighborhoods that cross the left or right border are sampled from the opposite side of the panorama. This prevents the autoencoder from injecting artificial boundary artifacts into latent features and decoded frames.

4.4 Random Roll Yaw

ERP panoramas have no canonical yaw orientation: horizontally rolling a panorama corresponds to rotating the world around the vertical axis. If the model only sees the yaw distribution in the collected videos, it may overfit to dataset-specific orientations and become less robust under user-specified trajectories. Random Roll Yaw augments each training sample with a yaw-equivalent version by rolling the ERP video and applying the same yaw rotation to the camera trajectory. Given a horizontal roll s, the augmented video and camera-to-world pose are

$$I'_t(u,v) = I_t((u-s) \bmod W, v), \qquad T'_t = R_y(2\pi s/W)\, T_t. \tag{3}$$

This keeps the video and control signal geometrically aligned while exposing the model to diverse trajectory orientations for the same scene.

4.5 Panoramic Plücker Embedding

Perspective camera-control methods usually describe camera motion through pinhole rays parameterized by camera intrinsics. This representation is not suitable for ERP panoramas, where each pixel corresponds to a direction on the viewing sphere rather than a ray through a perspective image plane. We therefore formulate the control signal as a panoramic Plücker field: ERP pixels are converted to spherical rays and then transformed by the target camera poses. For an ERP pixel (u, v), we first compute its longitude and latitude,

$$\lambda_u = 2\pi \frac{u + 1/2}{W} - \pi, \qquad \phi_v = \frac{\pi}{2} - \pi \frac{v + 1/2}{H}, \tag{4}$$

and obtain the camera-space ray direction

$$d_{\text{cam}}(u,v) = \begin{bmatrix} \cos\phi_v \sin\lambda_u \\ \sin\phi_v \\ \cos\phi_v \cos\lambda_u \end{bmatrix}. \tag{5}$$

With camera pose (R_t, o_t), the panoramic Plücker condition is

$$d_t = R_t d_{\text{cam}}, \qquad m_t = o_t \times d_t, \qquad L_t(u,v) = \left[d_t; m_t\right]. \tag{6}$$

This provides trajectory conditioning that is compatible with panoramic geometry while reusing the baseline's ray-based control interface.

5 Experiments

5.1 Evaluation of Dataset Quality

We conduct a user study to evaluate the annotation quality of MUGEN from three complementary aspects: long-form text descriptions, structured category labels, and camera trajectories. We randomly sample 1,000 one-minute clips from MUGEN and recruit 10 volunteers for human verification. For each aspect, every sampled

Table 1. Experimental results on generated video quality and camera control accuracy. (I) Ablation of the three ERP-aware components in Wan360; (II) disentangled evaluation of model and data; (III) comparison with other panoramic video generation methods. ↑ / ↓ indicates whether higher / lower is better.

Model	FVD ↓	SSIM ↑	LPIPS ↓	Consistency ↑	Quality ↑	Dynamic ↑	PSNR ↑	TransErr ↓
(I) Ablation of the three ERP-aware components.								
Wan360 (w/o Periodic Longitude RoPE)	491.2	0.435	0.393	0.912	0.459	**0.740**	14.58	0.192
Wan360 (w/o ERP-Aware Padding)	478.5	0.446	0.378	**0.915**	0.457	0.710	14.79	0.188
Wan360 (w/o Random Roll Yaw)	486.9	0.439	0.387	0.912	0.456	0.720	14.65	0.215
Wan360 (Ours, full)	**476.6**	**0.449**	**0.377**	**0.915**	**0.463**	0.720	**14.86**	**0.184**
(II) Disentangled evaluation of model and data.								
GenEX [Lu et al. 2025]	1359	0.376	0.617	0.763	0.304	**0.891**	13.13	–
Wan360 (GenEX's data)	999.5	0.340	0.493	0.872	0.387	0.825	13.18	–
ViewPoint [Fang et al. 2025]	1676	0.297	0.707	0.861	0.332	0.650	10.85	–
Wan360 (ViewPoint's data)	952.3	0.361	0.429	0.896	0.413	0.550	14.00	–
Wan360 (Ours)	**476.6**	**0.449**	**0.377**	**0.915**	**0.463**	0.720	**14.86**	**0.184**
(III) Comparison with other methods.								
4K4DGen [Li et al. 2024]	1541	0.345	0.494	**0.951**	0.421	0.275	13.02	–
DynamicScaler [Liu et al. 2025]	1941	0.269	0.641	0.886	0.423	0.397	10.84	–
CubeComposer [Li et al. 2026]	1579	0.305	0.579	0.918	0.395	0.100	11.46	–
OmniRoam [Liu et al. 2026]	640.0	0.410	0.463	0.901	0.430	**0.723**	13.77	0.251
Wan360 (Ours)	**476.6**	**0.449**	**0.377**	0.915	**0.463**	0.720	**14.86**	**0.184**

clip is independently reviewed by all 10 volunteers. An annotation is considered valid if at least seven volunteers judge it to be correct or usable.

5.1.1 Text Descriptions. Volunteers judge whether each long-form description matches the clip content, events, and camera motion; hallucinated or contradictory descriptions are marked as invalid. 94.7% of the sampled descriptions are judged to be accurate, indicating that the text annotations provide reliable semantic supervision for panoramic video generation.

5.1.2 Category Labels. Volunteers judge whether the provided category labels are supported by the video; ambiguous or visually unverifiable labels are treated as invalid. The final valid ratio reaches 95.3%, showing that the automatically generated category labels are sufficiently accurate for dataset analysis and controlled training.

5.1.3 Camera Trajectories. Volunteers inspect trajectory-overlaid clips and judge whether each trajectory is plausible and aligned with the observed camera motion; obvious drift or wrong-direction cases are marked as unusable. The resulting usable trajectory ratio is 92.4%, validating that MUGEN provides reliable camera-control annotations for interactive panoramic video generation.

5.2 Experimental Setup

5.2.1 Training Details. Wan360 is fine-tuned from the Wan2.2-Fun-5B-Control-Camera [Wan et al. 2025] baseline. We fine-tune it on MUGEN-HQ to generate 161 frames at 1920×960 resolution, sampled at 16 FPS from the 30 FPS source videos. Training is conducted on 8×NVIDIA H200 GPUs for 10 epochs with a learning rate of $\mathbf{1{\times}10^{-5}}$.

5.2.2 Evaluation Data. We randomly select 200 video samples that are excluded from training. From them, we curate a final test set of 100 videos by stratifying the samples according to camera trajectory patterns and scene categories.

5.2.3 Metrics. For reconstruction-oriented quality, we report FVD [Unterthiner et al. 2018], SSIM [Wang et al. 2004], LPIPS [Zhang et al. 2018], and PSNR against held-out reference videos. For perceptual and temporal quality, we use VBench++ [Huang et al. 2024]. For camera control, following CamCtrl [He et al. 2024a], we annotate the trajectory of each generated video using ViPE [Huang et al. 2025] and compute the translation error (*TransErr*) against the input trajectory.

5.3 Evaluation of Model Performance

5.3.1 Ablation Study. Block (I) of Table 1 evaluates the three ERP-aware components in Wan360. Removing Periodic Longitude RoPE, ERP-aware padding, or random roll yaw weakens the overall balance between video quality and camera control. The full model achieves the best overall score, indicating that the three components are complementary for fine-tuning a perspective video generation baseline for panoramic video generation.

5.3.2 Disentangling Model and Data. Block (II) isolates the contributions of architecture and data. We train Wan360 using the same training recipe while replacing MUGEN-HQ with data from GenEX [Lu et al. 2025] or ViewPoint [Fang et al. 2025]. Under the same evaluation protocol, Wan360 trained on these alternative datasets improves

several metrics over the corresponding original methods, but remains behind Wan360 trained on MUGEN-HQ. This result suggests that Wan360 contributes meaningful model-side gains, while the scale, diversity, and annotation quality of MUGEN-HQ are essential for the final performance.

5.3.3 Comparison with Existing Methods. Block (III) evaluates Wan360 against representative panoramic video generation methods under the same held-out test set. Compared with prior methods, Wan360 substantially reduces FVD and LPIPS while improving SSIM, PSNR, and video quality, indicating better frame-level fidelity and temporal realism. Among methods with explicit camera-control evaluation, Wan360 also achieves the lowest TransErr, showing more accurate trajectory following in dynamic real-world panoramas.

5.4 Qualitative Examples

Fig. 6 provides qualitative comparisons with representative methods. 4K4DGen [Li et al. 2024] often produces limited apparent motion, GenEX [Lu et al. 2025] introduce artifacts and geometric distortions under large motion, CubeComposer [Li et al. 2026] tends to produce less dynamic videos, and OmniRoam [Liu et al. 2026] is constrained by static scene assumptions. In contrast, Wan360 better preserves panoramic structure, visual details, and temporally coherent motion. Fig. 7 further compares Wan360 with OmniRoam under explicit target trajectories, showing that Wan360 follows the prescribed motion while maintaining dynamic real-world content. Finally, Fig. 8 shows examples generated from the same input panorama under different camera trajectories, demonstrating that Wan360 can produce trajectory-dependent panoramic videos with consistent scene appearance.

6 Conclusion

In this work, we take a step toward interactive panoramic world exploration, where the central goal is to generate immersive 360° videos that remain coherent while following user-specified camera trajectories in dynamic real-world scenes. This task requires both suitable annotated data and a model that can respect panoramic geometry under camera control. To this end, MUGEN provides large-scale, high-quality real-world panoramic videos with rich semantic and geometric annotations, including explicit camera trajectories for controllable generation. Built on MUGEN, Wan360 fine-tunes a perspective camera-control video generation baseline for ERP panoramas through periodic longitude RoPE, ERP-aware padding, random roll yaw, and a panoramic Plücker embedding. Experiments show that MUGEN provides effective data support for the task, and that Wan360 generates panoramic videos with strong visual quality, temporal coherence, and trajectory controllability. The proposed MUGEN and Wan360 establish a practical foundation for camera-controlled interactive panoramic world exploration in real-world environments.

6.1 Limitations

We use ViPE [Huang et al. 2025] to perform 3D reconstruction on videos generated by Wan360. In static scenes, the reconstructed scene structure and relative object positions remain generally stable, while the estimated camera trajectories are smooth and continuous. However, strict 3D consistency is not guaranteed, particularly in dynamic scenes with independently moving objects. Explicitly enforcing geometric and temporal consistency remains an important direction for future work. Wan360 currently generates fixed-length clips and does not yet support real-time or unbounded long-horizon generation, where error accumulation remains an open challenge. In addition, MUGEN's data primarily comes from the real world. In future work, we will consider extending it to other domains, such as animation and games.

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Fig. 6. Qualitative comparison of panoramic video generation methods. Wan360 produces panoramic videos with higher visual fidelity, better temporal consistency, and more realistic dynamics.

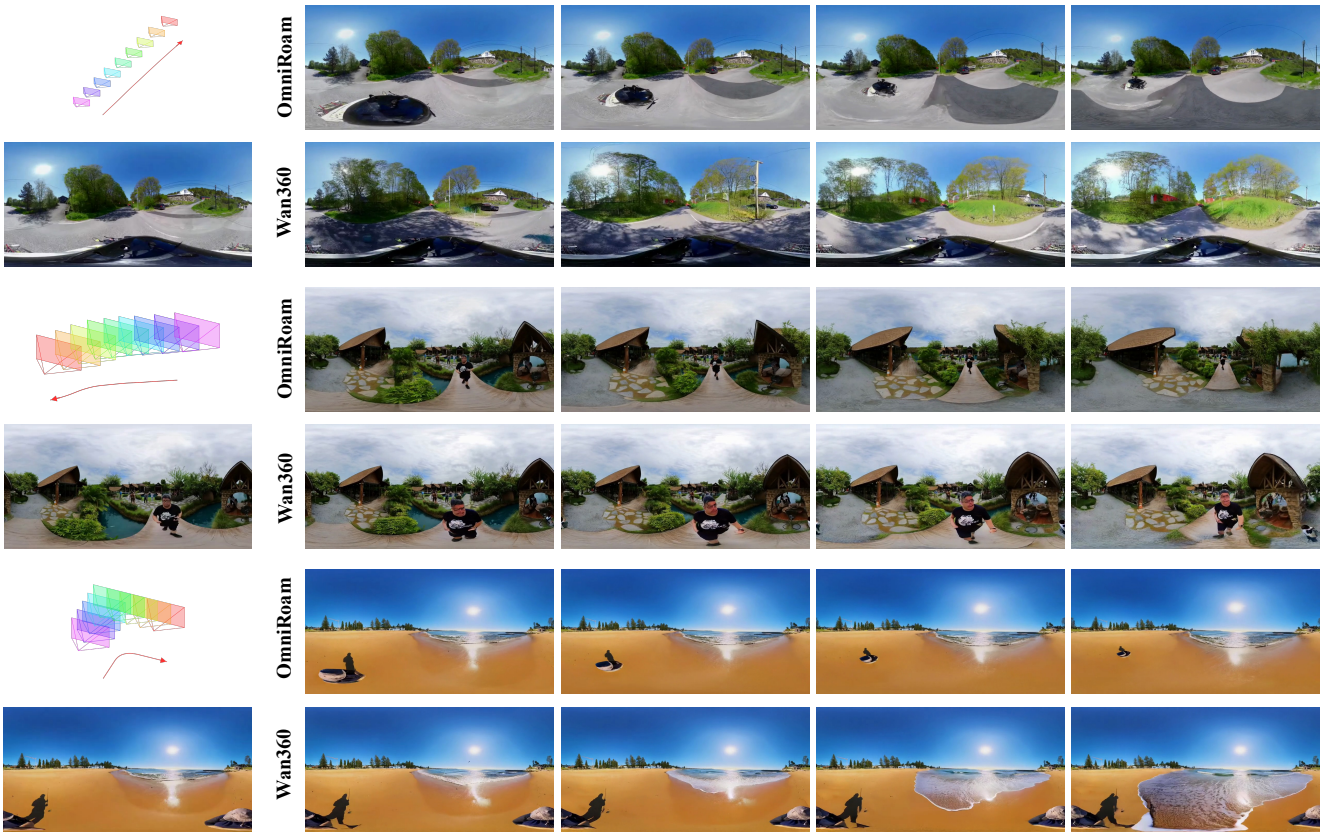

Fig. 7. Qualitative comparison under target camera trajectories. The left column shows the input panorama and target trajectory, while the right columns compare generated sequences from OmniRoam [Liu et al. 2026] and Wan360.

Fig. 8. Qualitative results of Wan360 under different target trajectories for 10s. Given the same input panorama, Wan360 produces distinct video sequences aligned with different camera motions while maintaining consistent scene appearance.