

# Coarse-to-Real: Generative Rendering for Populated Dynamic Scenes

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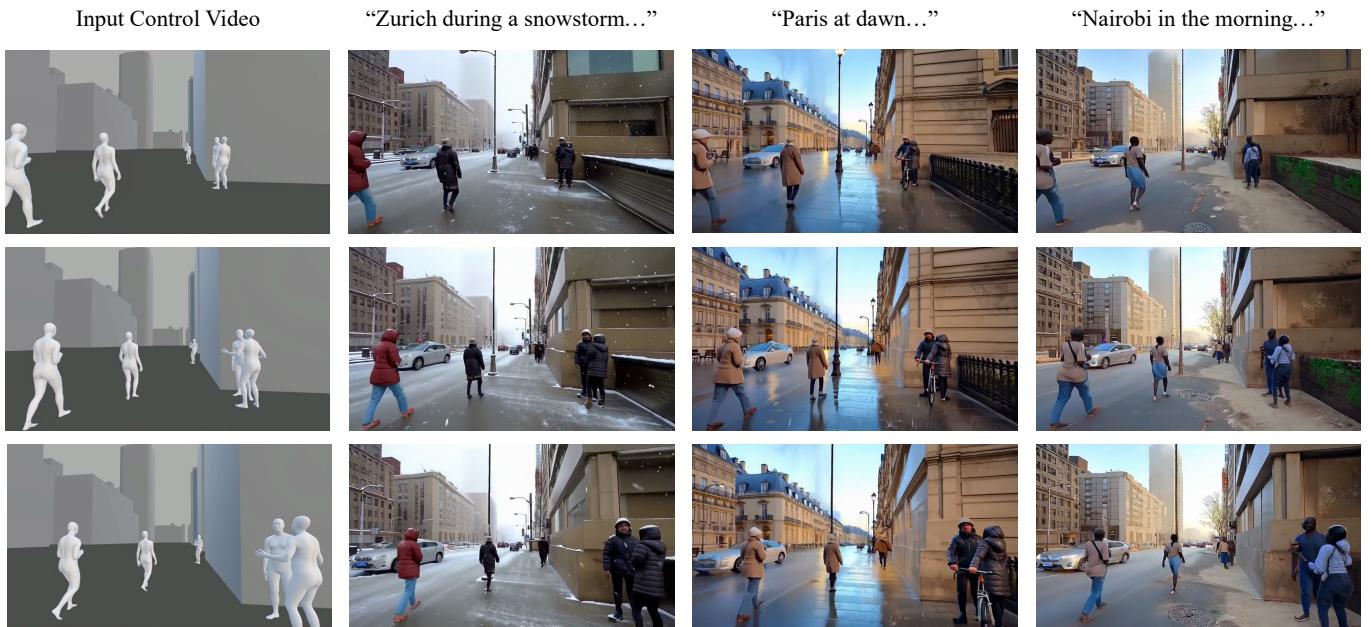


Fig. 1. C2R (Coarse-to-Real) transforms a single coarse 3D control video (left) into diverse scenes via text prompts, varying texture detail, lighting, weather, location, dynamics and background crowds while maintaining consistent camera motion and human trajectories.

Traditional rendering pipelines rely on complex assets, accurate materials and lighting, and substantial computational resources to produce realistic imagery, yet they still face challenges in scalability and realism for populated dynamic scenes. We present C2R (Coarse-to-Real), a generative rendering framework that synthesizes real-style urban crowd videos from coarse 3D simulations. Our approach uses coarse 3D renderings to explicitly control scene layout, camera motion, and human trajectories, while a learned neural renderer generates realistic appearance, lighting, and fine-scale dynamics guided by text prompts. To overcome the lack of paired training data between coarse simulations and real videos, we adopt a two-phase mixed CG-real training strategy that learns a strong generative prior from large-scale real footage and introduces controllability through shared implicit spatio-temporal features across domains. The resulting system supports

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coarse-to-fine control, generalizes across diverse CG and game inputs, and produces temporally consistent, controllable, and realistic urban scene videos from minimal 3D input. We will release the model and project webpage at <https://gonzalognogales.github.io/coarse2real/>.

CCS Concepts: • Computing methodologies → Rendering; Computer vision; Neural networks; Animation.

Additional Key Words and Phrases: Neural rendering, Generative video synthesis, Controllable video synthesis, Domain adaptation

## 1 Introduction

Rendering populated realistic urban scenes with dynamic camera trajectories and complex group motion remains expensive and difficult in traditional computer graphics (CG) pipelines. Achieving realism typically requires high-quality assets, detailed materials, accurate lighting, and carefully tuned simulations, leading to substantial production cost and memory overhead, yet often still exhibiting a gap from real-world appearance. Recent advances in generative text-and image-to-video models offer an alternative [Chen et al. 2023b; Ho et al. 2022; Ruan et al. 2023; Singer et al. 2023; Yang et al. 2025],

but existing methods struggle with scenes involving multiple interacting humans, long-term temporal consistency, and coherent camera motion. Purely text-based control is insufficient for precisely specifying scene structure and dynamics, and image-conditioned approaches [Geng et al. 2025], including recent commercial systems such as Sora, remain limited to simple and similar camera positions for scenes involving complex crowd dynamics, as shown in the appendix. Video-to-video models [Cheng et al. 2024; Li et al. 2024; NVIDIA et al. 2025; Wang et al. 2023] combined with ControlNet [Zhang et al. 2023] offer promising and more controllable alternatives, but they usually use strong geometric control signals that over-constrains the generation and the expressivity of the output video.

A key observation motivating this work is that many challenges related to dynamic video generation are trivial in 3D, while many of the most expensive aspects of 3D rendering are naturally handled by data-driven models. Camera motion, spatial structure, and temporal consistency are explicit and stable in coarse 3D scenarios, whereas detailed geometry, textures, materials, lighting, and visual diversity are costly to author and render. This complementary relationship motivates a hybrid paradigm, where coarse 3D simulation provides structural and dynamic control, and a learned generative model functions as a renderer that synthesizes realistic appearance.

We introduce **C2R (Coarse-to-Real)**, a generative rendering framework that produces real-style populated urban videos from coarse 3D inputs. C2R takes temporally consistent coarse renderings encoding scene layout, camera trajectories, and human motion, and enriches them with realistic textures, lighting, and fine-scale dynamics learned from real-world video data. The framework offers flexible control, including inpainting clothing, hair, buildings, and environmental details beyond the input structure, adjusting the strength of generative rendering, and supporting coarse-to-fine inputs. Importantly, C2R is agnostic to specific human templates and asset formats, allowing it to generalize across a wide range of CG, game, and animation scenes.

A central technical challenge is the absence of paired training data between coarse CG simulations and real-world videos. To address this challenge, we propose a mixed CG-real training strategy based on a two-phase learning framework. In the first phase, the model is trained on large-scale unpaired real-world videos to learn a strong photorealistic generative prior. In the second phase, controllability is introduced by grounding this prior using *implicit spatio-temporal features* extracted from both real and synthetic inputs, enabling the model to interpret structural cues in a shared feature space across domains despite the absence of explicit pairing, and to adaptively hallucinate content based on the level of detail present in the input. A small proportion of synthetic paired coarse–fine data anchors the correspondence between coarse structure and realistic appearance, while the dominance of real data prevents contamination by CG-specific artifacts. To support diverse generation conditions, we curate and annotate footage from five continents, covering a wide range of cities, weather conditions, lighting, and clothing styles. We evaluate different latent feature insertion strategies and demonstrate that C2R produces temporally consistent, controllable, and realistic urban scene renderings from minimal 3D simulation.

## 2 Related Works

We review research relevant to the high-quality synthesis of populated urban videos, from the perspective of traditional computer graphics pipelines (Sec.2.1), video and world models (Sec.2.2) and controllable video generation techniques (Sec.2.3). Our discussion emphasizes the unique challenges of maintaining structural control and temporal consistency in dynamic scenes with complex crowd interactions.

### 2.1 Traditional CG for Dynamic Populated Scenes

Rendering populated urban environments with dynamic camera trajectories and complex group motion is among the most resource-intensive tasks in traditional computer graphics pipelines. Achieving high-fidelity realism necessitates extensive libraries of quality assets, including diverse 3D human meshes, detailed architecture, and physically based materials. Generating these components typically requires expert manual modeling or costly 3D scanning [Anguelov et al. 2005; Loper et al. 2015]. As scene complexity scales, the memory overhead for high-resolution textures and geometry strains computational resources and compromises rendering efficiency. Beyond static assets, animating large crowds requires simulating intricate group behaviors and social interactions [Helbing and Molnar 1995]. While traditional techniques like skeletal animation and motion graphs [Kovar et al. 2002] provide stability, they often struggle to produce naturalistic motion and vivid dynamics. Consequently, significant visual discrepancies compared to real-world appearances persist—particularly for large-scale crowds with diverse clothing and hair patterns—rendering the scalable authoring of realistic urban scenes practically challenging. Unlike these resource-intensive pipelines, our C2R framework leverages coarse 3D simulations as lightweight structural proxies, delegating the synthesis of photorealistic details and vivid dynamics to a data-driven generative renderer.

### 2.2 Video and World Models

Recent advances in text-to-video [Chen et al. 2023b; Ho et al. 2022; Ruan et al. 2023; Singer et al. 2023; Wan et al. 2025; Yang et al. 2025] and image-to-video [Chen et al. 2023a; Esser et al. 2023] generation offer a compelling alternative by synthesizing realistic imagery directly from data. However, existing generative video models struggle to reliably produce scenes with multiple interacting humans, long-term temporal consistency, or coherent camera motion. In Figure 12 in the appendix, SORA and WAN 2.1 [Wan et al. 2025] show limited controllability over human motion and camera trajectories, and tend to generate similar viewing angles across populated urban scenes. Moreover, purely text-based control is insufficient for precisely specifying scene structure, camera trajectories, and crowd dynamics, while image-conditioned approaches inherit the limitations of the input frame and offer limited control over motion and layout. As a result, current video generation systems fall short as practical tools for authoring structured, dynamic urban scenes.

To provide the structural grounding required for such urban scenes, a parallel line of research has emerged concision on world models. Unlike purely pixel-based generators, these models aim to leverage explicit 3D priors [Kerbl et al. 2023; Wang et al. 2024] to build consistent traversable scenes. For instance, WorldGen [Wang

et al. 2025] utilizes procedural generation to ensure global layout stability and precise camera control. However, while these models excel at maintaining static structure, they often struggle to capture the vivid, stochastic dynamics of populated urban crowds.

Unlike these approaches, C2R does not attempt to reconstruct a 3D world or rely on purely procedural logic. Instead, we leverage coarse 3D simulations as structural proxies, formulating the computationally expensive task of rendering procedure to generate photorealistic textures, physically plausible lighting, and fine-grained crowd dynamics. This hybrid formulation allows C2R to bypass the "sim-to-real" gap that persists in traditional CG and the lack of structural control in monolithic video models.

### 2.3 Controllable Video Generation

To bridge the gap between generative realism and structural precision, several lines of work have explored explicit conditioning for video synthesis: (1) One of the strategies focuses on sparse motion and camera guidance. Methods such as CameraCtrl [He et al. 2025], GEN3C [Ren et al. 2025], and Wan-Move [Chu et al. 2025] incorporate explicit camera parameters or trajectories to guide the denoising process. Similarly, motion-driven approaches like Motion Prompting [Geng et al. 2025] and MCDiff [Chen et al. 2023a] utilize user-defined strokes or points to specify movement. While effective for single-subject scenes, these methods often struggle with the combinatorial complexity of crowded environments, where multiple characters interact with independent and varying velocities. Furthermore, sparse signals often fail to ground the global scene layout as robustly as a 3D proxy. (2) Another strategy involves dense structural conditioning, often referred to video-to-video (vid2vid) synthesis. Existing frameworks [Esser et al. 2023; NVIDIA et al. 2025; Wang et al. 2018] use per-frame geometric cues, e.g., depth maps, Canny edges, or semantic layouts, to transform input sequences. However, these strong geometric signals often over-constrain the model expressivity, forcing the output to strictly follow the input geometry and preventing the generative renderer from adding "vivid dynamics".

Our C2R takes a different path by leveraging an implicit spatial-temporal feature representation. Unlike previous methods that rely on either sparse trajectories or rigid dense maps, C2R utilizes coarse 3D representations as lightweight structural proxies. This allows our framework to maintain the global stability and intent of the 3D scene while giving the generative model the freedom to generate high-fidelity textures, physically plausible lighting, and fine-grained crowd dynamics learned from real-world footage.

## 3 Method

### 3.1 Overview and Design Choices

Our goal is to generate vivid and real-styled videos that follow the camera motion and scene dynamics of coarse 3D or game-engine renders. This setting introduces three challenges: (1) coarse renders provide reliable structure but lack realistic appearance; (2) paired supervision between coarse 3D inputs and photorealistic targets is only available for CG data, while real videos are abundant but lack aligned control signals, requiring a bridge between real and synthetic inputs; and (3) explicit structural controls (e.g., depth,

edges, poses) over-constrain generation by entangling appearance with structure, often leading to *feature leakage*, where the model bypasses synthesis and reconstructs the control input.

To address these challenges, we decouple photorealistic prior learning from structural controllability using a two-stage training strategy. We first learn a high-fidelity generative prior from large-scale real videos without structural conditioning. We then introduce controllability by grounding this prior using *implicit spatio-temporal features* extracted from both real and synthetic inputs and mapped into a shared feature space via a lightweight adapter. This design yields adaptive behavior: coarse inputs allow flexible synthesis, while richer inputs naturally enforce stronger adherence to motion and layout.

### 3.2 Architecture Preliminaries

We build on WAN 2.1 [Wan et al. 2025] and denote its VAE encoder and decoder by  $E$  and  $D$ , and its diffusion backbone (Diffusion Transformer) by DiT with parameters  $\theta$ . Text conditioning is provided by a pretrained T5-XXL encoder T5 [Raffel et al. 2020] that maps a prompt  $c$  to an embedding  $e_{\text{text}} = T5(c)$ . For control signals, we extract patchwise features using a pretrained DINOv3 ViT [Siméoni et al. 2025], and train an adapter  $A$  that projects these features into the diffusion latent space.

### 3.3 Stage I: Generative Distribution Alignment

**Motivation.** Coarse control signals alone cannot teach photorealistic appearance. We therefore first adapt the diffusion backbone to the target "realistic urban video" distribution so that it learns lighting, materials, and natural motion before being asked to follow coarse structure.

**Training.** In this stage, we fine-tune only the diffusion backbone  $\theta$  on real-world videos, while freezing the VAE  $E$ ,  $D$  and the text encoder. Given a real video  $x$  and its corresponding prompt embedding  $e_{\text{text}}$ , we first encode the video to latent representation:

$$z_0 = E(x). \quad (1)$$

Then, following the Flow Matching formulation applied in Wan 2.1, we sample a timestep  $t \in [0, T]$  and apply the standard diffusion process by adding Gaussian noise  $\epsilon \sim N(0, I)$  to obtain the noisy latents  $z_t = (1-t)z_0 + t\epsilon$ . The model is trained to predict the velocity field:

$$v_t = \text{DiT}_\theta(z_t, t, e_{\text{text}}), \quad (2)$$

where the objective is defined as:

$$L_{\text{FM}} = \mathbb{E}_{z_0, t, e_{\text{text}}} \left[ \left\| \text{DiT}_\theta(z_t, t, e_{\text{text}}) - (\epsilon - z_0) \right\|_2^2 \right]. \quad (3)$$

At inference, we can predict the denoised latents  $\hat{z}_0$  through an iterative sampling process, and the final clean video results can be obtained by the vae decoder via  $\hat{x} = D(\hat{z}_0)$ .

### 3.4 Stage II: Spatio-Temporal Control Grounding

**Motivation.** After Stage I, the model generates realistic videos but lacks controllability. Stage II teaches the model to interpret coarse structure *without* forcing an explicit signal (e.g., depth/edges) as in ControlNet [Zhang et al. 2023] that would rigidly constrain silhouettes. Instead, we use *implicit* features from a self-supervised

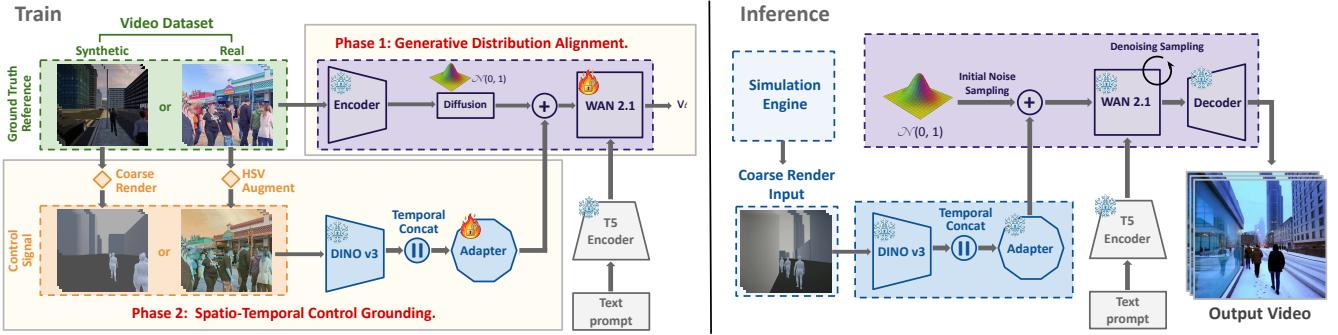


Fig. 2. **Overview of C2R** A two-stage framework decouples photorealistic prior learning from structural control: the diffusion backbone is first adapted to real videos, then grounded using implicit spatio-temporal features from mixed real and synthetic data. At inference, a coarse render and text prompt guide denoising to synthesize realistic videos following input motion and layout.

encoder that preserve layout and motion while being less tied to pixel appearance.

**Training.** We freeze the tuned diffusion backbone and train only the control pathway, i.e., the adapter  $A$  (and any lightweight temporal aggregation described below). Let  $\mathbf{x}_{\text{ctrl}}$  be the control-branch input. We extract features frame-by-frame:

$$\mathbf{f}_i = \text{DINO}(\mathbf{x}_{\text{ctrl}}^{(i)}), \quad i = 1, \dots, N, \quad (4)$$

and construct a spatio-temporal representation by temporal concatenation:

$$\mathbf{f}_{1:N} = \text{Concat}_i(\mathbf{f}_1, \dots, \mathbf{f}_N). \quad (5)$$

The adapter projects these features to a latent guidance tensor:

$$\hat{\mathbf{z}}_{\text{ctrl}} = A(\mathbf{f}_{1:N}). \quad (6)$$

We inject the control guidance into the diffusion latent by element-wise addition:

$$\hat{\mathbf{z}}_t = \mathbf{z}_t + \hat{\mathbf{z}}_{\text{ctrl}}. \quad (7)$$

Our experiments show that simple feature addition matches or outperforms multi-head cross-attention for integrating control features. Similar to Stage I, the diffusion backbone then denoises  $\hat{\mathbf{z}}_t$  conditioned on text, and we optimize  $A$  with the same diffusion objective (Eq. 3) on the corresponding target video.

### 3.5 Mixed-Domain Data as a Domain-Bridging Supervision Signal

A controllable video generation model would ideally be trained on paired data, where a coarse 3D input video is matched with a photorealistic target. In practice, such paired supervision can only be obtained from computer-generated (CG) data, which is expensive to produce, limited in diversity, and constrained by rendering fidelity. In contrast, real-world videos are abundant and available at vastly larger scale, exhibiting rich variations in appearance, motion, and camera trajectories that are difficult to reproduce synthetically. To exploit this diversity and improve photorealism, we deliberately train C2R with *hundreds of times more real videos than synthetic ones*, using real data to shape a strong generative prior and synthetic data to provide sparse but essential paired supervision.

To address this challenge, we design the training pipeline such that both real videos and synthetic coarse renders are mapped into a *common spatio-temporal feature space*. In this space, control signals extracted from real videos and from coarse 3D simulations are encouraged to be compatible, enabling joint training despite their very different origins. Synthetic paired data anchors this space by explicitly linking coarse geometry to high-quality targets, while real videos populate it densely and enrich the learned generative distribution. Please refer to the appendix for how we collect and annotate the synthetic and real dataset.

### 3.6 Adaptive Spatio-Temporal Control from Implicit Features

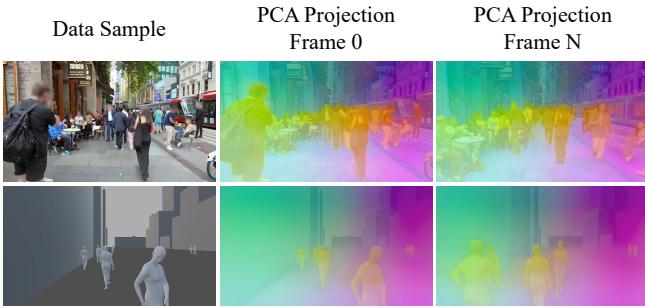
A central challenge in controllable video generation is extracting spatio-temporal control signals that generalize across real and synthetic domains. Explicit structural representations such as depth, edges, optical flow, or poses [Cheng et al. 2024; Li et al. 2024; NVIDIA et al. 2025; Wang et al. 2023] often entangle geometry with appearance, especially in real videos rich in texture and fine detail. As a result, they tend to over-constrain generation and encourage direct reconstruction rather than synthesis.

To address this, we adopt an *implicit* spatio-temporal representation that preserves scene layout and motion while abstracting away low-level appearance. We extract dense patch-level features using a pretrained self-supervised vision encoder [Siméoni et al. 2025] and aggregate them temporally to form a spatio-temporal feature grid. These features (visualized in Figure 3) are appearance-robust and semantically structured, making them suitable as a shared control representation for both real videos and synthetic coarse renders.

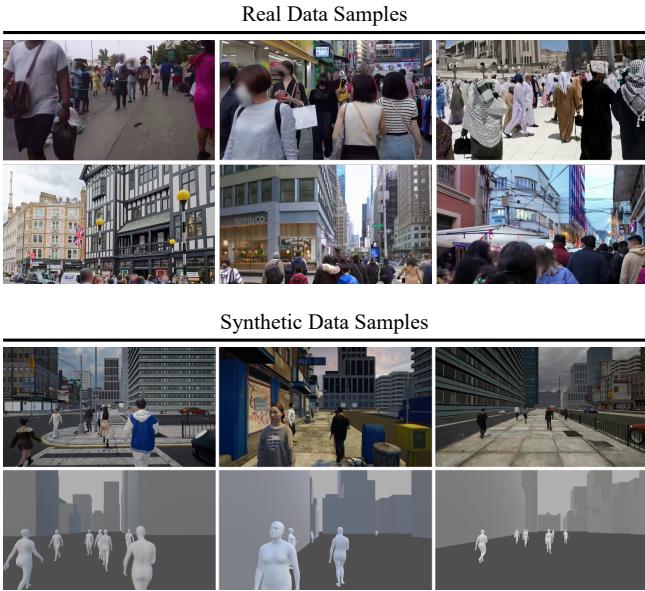
To further reduce appearance leakage when using real videos, we apply a video-consistent HSV transformation to the control branch during training. This suppresses color and texture correlations while preserving geometric structure and temporal coherence, encouraging the control signal to focus on layout and dynamics rather than pixel fidelity. Details can be found in the appendix.

This implicit formulation naturally yields *adaptive control*. When the input is very coarse, the extracted features provide high-level structural cues, allowing the model to freely hallucinate fine-scale

details and secondary motion. When richer structural information is present, the same mechanism enforces stronger adherence to the input motion and spatial configuration. As a result, C2R supports a wide range of inputs—from low-poly game-engine videos to more detailed simulations—without requiring different control strategies or hand-crafted rules.



**Fig. 3. DINOv3 features provide a domain-robust and temporally stable control signal.** We visualize patch embeddings using a *global* PCA projection computed on a mixed subset of real and synthetic samples, then reused across videos. Similar PCA colors across real and synthetic inputs indicate that DINOv3 aligns corresponding structural elements despite large appearance gaps. Color stability across time suggests temporal coherence even when features are extracted per-frame, supporting spatio-temporal control.



**Fig. 4. Dataset samples and domain-bridging strategy.** Top: real-world videos used in Stage I to learn a high-fidelity generative prior across diverse cities, clothing styles, weather, and camera motion. Bottom: synthetic HQ/coarse pairs used in Stage II to explicitly teach correspondence between coarse geometry (control) and photorealistic appearance (target).

### 3.7 Inference

As shown in Fig. 2, at inference time, given a coarse control video  $\mathbf{x}_{\text{coarse}}$  and a text prompt  $\mathbf{c}$ , we compute a control latent  $\hat{\mathbf{z}}_{\text{ctrl}} = A(\text{DINO}(\mathbf{x}_{\text{coarse}}))$  and a text embedding  $\mathbf{e}_{\text{text}} = \text{T5}(\mathbf{c})$ . We then perform standard diffusion sampling using a Flow Matching (Rectified Flow) sampler, which is solved with a first-order Euler integrator, starting from Gaussian noise  $\mathbf{z}T \sim \mathcal{N}(0, I)$ . At each denoising step, control is injected via additive fusion (Eq. 7), while textual conditioning is incorporated through cross-attention. After the final step, the decoded output is obtained as  $\hat{\mathbf{x}} = D(\hat{\mathbf{z}}_0)$ .

**3.7.1 Guidance control.** To balance structural faithfulness and textual alignment, we use Adaptive Prompt Guidance (APG) [Castillo et al. 2025] during sampling. APG dynamically scales conditioning contributions, allowing the model to deviate from coarse input appearance (e.g., colors/textures) while maintaining motion and layout.

## 4 Experiments

In this section, we present a comprehensive evaluation of C2R to assess its performance in synthesizing high-fidelity, controllable urban videos. We utilize a training dataset consisting of 240k clips of real-world footage and 1.3k clips of synthetic data, with specific details regarding collection and annotation provided in Figure 4 and the Appendix. Our evaluation begins by introducing the quantitative metrics used to measure both semantic alignment and structural fidelity. To further validate our architectural and data-driven design choices, we conduct a series of ablation studies focusing on the mixed-domain data ratio, our additive feature injection strategy, and the necessity of HSV decorrelation. We then provide qualitative evidence of the model’s adaptive capacity to handle varied levels of input geometry, ranging from low-poly simulations to more detailed renders. Finally, compare our framework against the only publicly available state-of-the-art baseline to demonstrate our improvements in visual expressivity.

### 4.1 Metrics

We evaluate our method along two complementary axes: *text-video alignment* and *structural consistency*. To measure how well the generated video follows the input motion and structure, we use VE-Bench [Sun et al. 2025], which is designed for video editing and control-based evaluation. While VE-Bench is applicable to our setting, it may penalize large appearance changes and favor conservative edits that closely preserve the source. To account for this limitation, we additionally report VQAScore [Lin et al. 2025], a text-video alignment metric that directly evaluates prompt adherence. Using both metrics together provides a more balanced quantitative assessment of controllability and semantic alignment.

### 4.2 Ablations

**4.2.1 Data training mixture.** We study how the sampling ratio of real and synthetic data during training influences the trade-off between structural controllability (VE-Bench) and prompt adherence (VQAScore). For example, A ratio of 50% real + 50% synthetic indicates that, for each training batch, samples are drawn from the real and synthetic data pools with equal probability. Table 1 shows that,

| Model                            | VE-Bench↑     | VQAScore↑     |
|----------------------------------|---------------|---------------|
| WAN2.1 + ControlNet              | 0.0086        | 0.0478        |
| 100% synthetic                   | 0.4675        | <b>0.5242</b> |
| 50% real+50% real                | 0.4560        | <u>0.4537</u> |
| 95% real+5% synthetic            | 0.4809        | 0.4262        |
| 99% real+1% synthetic (our pick) | <u>0.5317</u> | 0.3420        |
| 100% real                        | <b>0.8090</b> | 0.1743        |
| 0 head (our pick)                | 0.5317        | <u>0.3420</u> |
| 1 head                           | <u>0.5837</u> | <b>0.3536</b> |
| 10 heads                         | <b>0.7893</b> | 0.0046        |

Table 1. Quantitative results on VE-Bench and VQAScore under different training data mixtures and control designs. **Bold** and underline indicate best and second best results, respectively.

as the proportion of real data increases from 0% to 99%, controllability improves steadily, while prompt adherence decreases accordingly. When training exclusively on real data (100%), the model achieves the highest VE-Bench score but suffers a sharp drop in VQAScore, reflecting a loss of generative flexibility and a tendency to strictly reproduce the input rather than hallucinate novel content. These trends are also evident in the qualitative results shown in Figure 5. Based on both quantitative and qualitative evaluations, we adopt a training strategy of 99% real and 1% synthetic data.

**4.2.2 Control feature injection strategy.** We inject DINO features from the control video into the first third of DiT blocks, which mainly influence structural control and global scene details. In Fig. 6 and Table 1, we compare alternative but computationally heavier strategies for integrating control features via projection heads: (0) direct addition of DINO features to noisy latents, (1) a single shared projection control head, and (10) dedicated projection control heads (1 per block). Surprisingly, direct addition (0 heads) achieves comparable quality to the 1-head approach, demonstrating that no extra learned projection is needed, training only the Adapter projection of the DINOv3 features to the diffusion latent space is enough. Meanwhile, per-block heads (10 heads) provide excessive capacity, causing the model to memorize training inputs rather than generalize. This shows that simple feature addition is sufficient, and adding learnable capacity either provides no benefit or actively harms performance.

**4.2.3 HSV Decorrelation.** We study the effect of HSV decorrelation in the control branch during Stage II training. Without HSV decorrelation, control features retain low-level appearance cues, causing the model to inherit colors and textures from the input video, which is undesirable when appearance should be synthesized from text and learned priors. Applying a video-consistent HSV transformation suppresses appearance correlations while preserving structure and temporal coherence, encouraging the control signal to focus on spatio-temporal layout and preventing appearance leakage, as illustrated in Fig. 7.

**4.2.4 Adaptive Coarse-to-fine control.** Fig. 8 shows that our method adapts control signals at different levels of geometric detail, from very coarse to relatively fine inputs. In all cases, the model respects the provided structure and adapts the generated content to the fidelity of the input geometry.

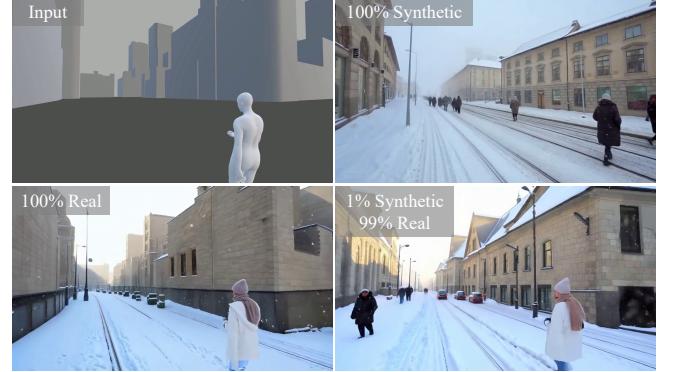


Fig. 5. **Effect of synthetic and real data proportion in training.** **Top:** Training exclusively on synthetic data results in poor alignment with the control input due to lack of variations in data distribution, while training only on real data improves structural alignment but yields weaker contextual richness. Mixing real and synthetic data combines the strengths of both, enabling faithful alignment while encouraging finer detail inpainting. **Bottom:** We further analyze different synthetic-real data ratios. A small amount of synthetic data (e.g., 1%) enhances detail generation while preserving strong control fidelity. As the proportion of synthetic data increases (5% and 50%), the model becomes progressively more creative but less constrained by the input control signal, leading to increased hallucination and deviation from the intended structure and motion.



Fig. 6. **Control signal injection strategies.** Direct addition (0 heads), single shared projection (1 head), and per-block projections (10 heads).



Fig. 7. Effect of W/ and W/o HSV decorrelation.

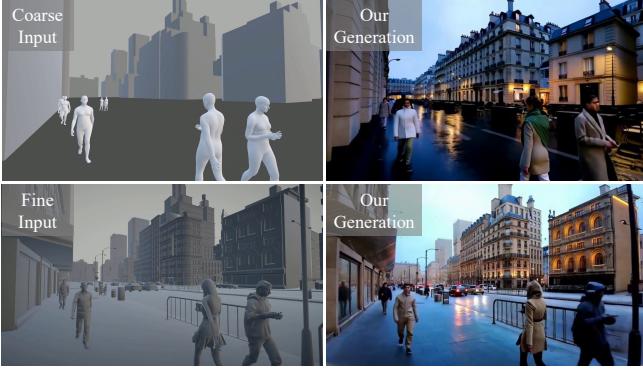


Fig. 8. Coarsening levels for driving signal. Given very coarse geometry (top), our model inpaints many details. Given fine geometry (bottom), it successfully follows the richer input signal.

#### 4.3 Comparisons

To evaluate the effectiveness of C2R, we compare our framework against current state-of-the-art controllable video generation baselines. Existing video-to-video models often rely on strong geometric control signals that can over-constrain the expressivity of the output. For our primary qualitative comparison, we utilize a baseline consisting of Wan 2.1 combined with an off-the-shelf ControlNet adapter [Team 2025]. We focus our evaluation on this specific configuration because it represents the only publicly available model capable of high-quality controllable video generation at this scale. While commercial systems such as Runway or Sora have demonstrated impressive results, these models are not publicly released and typically only showcase a limited number of curated examples, making a rigorous scientific evaluation of their actual performance and generalization capabilities impossible.

As illustrated in Fig. 9, C2R demonstrates a significant improvement in both visual fidelity and structural flexibility compared to the Wan 2.1 + ControlNet baseline. While the baseline adheres strictly to the provided geometric outlines, it often results in conservative appearance synthesis where both humans and environments lack the rich textures and lighting nuances characteristic of real-world urban footage. In contrast, our model yields more expressive videos where both humans and the scene exhibit a more realistic appearance, even when guided by the same coarse input signal.

To further explore these differences, we provide an additional comparison in the Appendix that evaluates C2R against both Wan 2.1 + ControlNet and unconditioned free generation from the Wan 2.1 backbone. This extended analysis demonstrates that C2R maintains the creative richness of a foundation model while providing the precise structural grounding.

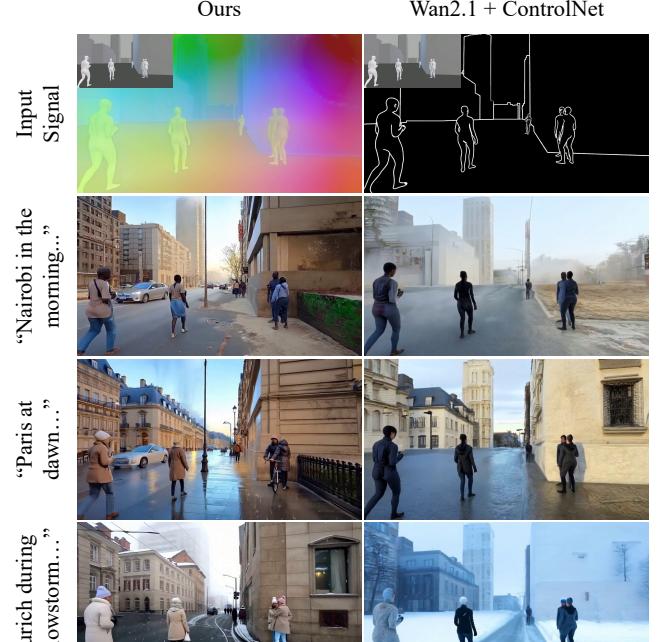


Fig. 9. Baseline comparison. We compare our results with a baseline trained with off-the-shelf ControlNet adaptor for Wan2.1. Our model yields more expressive videos, where both humans and scene exhibit more realistic appearance.

#### 5 Applications

Our framework is agnostic to the specific human and scene templates used in the control video and generalizes well beyond the training distribution. By operating on coarse 3D renderings and applying HSV augmentation during training, the model reduces dependence on appearance cues such as color, texture, and rendering style. This allows robust handling of inputs from different game engines, simulation pipelines, and lighting conditions while preserving camera motion and human trajectories.

As shown in Fig. 10, our method transforms low-poly game videos into realistic outputs while faithfully following the input motion and interactions. Notably, the input character is cartoon-styled and visually far from the neutral human models used during training, yet the generated video reproduces the same running and jumping motion with improved realism. Visual collision artifacts present in the low-poly input are also mitigated, resulting in more plausible contact between the character and the environment.

#### 6 Limitation and Future Works

Our method relies on coarse 3D inputs to guide scene layout, camera motion, and human dynamics. When the input geometry is extremely sparse or abstract, it may not provide sufficient structural cues to precisely control the desired layout or camera trajectory. In such cases, text prompts alone may be ambiguous and insufficient to fully disambiguate camera motion or character movement, as illustrated in Fig. 11. Future work includes incorporating more explicit control signals, such as camera motion directions, speed profiles, or



Fig. 10. Turn a low-poly Roblox game video into real-style. The character runs forward and jumps over a low wall.



Fig. 11. Limitation: very coarse input 3D structure might not be sufficient to guide the architecture and city layout as expected.

character movement constraints, to improve controllability. Additionally, the current framework operates in a non-autoregressive manner; extending the model to an autoregressive formulation could enable real-time generation and interactive applications.

## 7 Acknowledgement

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## A Appendix A

### A.1 Implementation Details

While our foundational Wan 14B model occasionally generates frames containing visible watermarks, we address this through an automated post-processing pipeline. Specifically, we employ specialized content-aware restoration tools to systematically detect and remove these artifacts, ensuring that the final synthesized videos maintain a clean and professional visual quality.

**A.1.1 Preventing Feature Leakage with Video-Consistent HSV Decorrelation.** **Problem.** DINO features are expressive: if the control branch receives the same pixels as the VAE branch, the adapter can pass appearance information that encourages reconstruction rather than synthesis.

**Solution.** For real videos during Stage II, we feed the same video  $\mathbf{x}$  to both branches, but apply a *video-consistent* random HSV transformation only to the control branch:

$$\mathbf{x}_{ctrl} = \text{HSV}(\mathbf{x}), \quad (8)$$

and compute  $\hat{\mathbf{z}}_{ctrl} = A(\text{DINO}(\mathbf{x}_{ctrl}))$ . By randomly shifting hue and scaling saturation/value consistently across frames, the adapter is forced to prioritize geometry and dynamics over pixel-level appearance. Compared to grayscale, HSV decorrelation avoids systematically biasing outputs toward muted colors and better preserves realistic color diversity. No augmentation is required at inference time.

### A.2 Existing Video Models for Populated Urban Scene Generation



Fig. 12. SORA (left column) and WAN (right column) show limited controllability over human motion and camera trajectories, and tend to generate similar viewing angles across populated urban scenes.

### A.3 Data Collection

We curate a large-scale dataset consisting of both synthetic and real-world videos to support training and evaluation.

For synthetic data generation, we use professional 3D content creation tools to simulate humans interacting within complex urban

3D environments. The scenes are of AAA visual quality, composed of fully textured city models with realistic geometry, materials, lighting, and post-processing effects, and populated with high-fidelity human assets obtained from detailed 3D scans [Super Dimension 2026]. City environments were obtained from Sketchfab and created by abhayexe under a Creative Commons license [abayexe 2024]. To enable paired supervision, each city environment is additionally converted into a corresponding coarse representation by approximating the volume of every building with simple flat geometric primitives (e.g., cuboids), producing a simplified city layout that preserves large-scale structure while removing fine visual detail. Vehicles are treated similarly, being replaced in the coarse domain by simple, untextured meshes that approximate their overall volume without appearance cues.

For character pairing, each high-quality scanned human model is matched with a coarse counterpart consisting of a simple, unclothed (naked) human body without hair or accessories. Both the full-quality and coarse characters are driven by the same motion data by retargeting identical Mixamo animations [Inc. 2013], ensuring precise alignment of motion, pose dynamics, and overall body structure across representations. This pairing strategy guarantees that differences between the full and coarse renders arise solely from appearance and geometric detail, rather than from motion discrepancies.

For each sample in the synthetic dataset, we randomly spawn a crowd of characters in a street region of the city, assign randomized textures and animations to the full-quality assets, and propagate the corresponding animations to their coarse counterparts. Two cameras with identical trajectories are then attached to a randomly selected character in the crowd and used to record a short replay sequence of 5 seconds. The full camera exclusively captures the high-quality assets, including detailed city geometry, vehicles, scanned characters, lighting, and post-processing effects, while the coarse camera records only the simplified elements: naked character bodies, a ground plane, and the coarse volumetric city and vehicle representations rendered with a uniform, neutral material (e.g., grayscale). Each iteration produces one paired data sample consisting of a full-quality video and its corresponding coarse video, enabling learning of fine-grained visual detail from structured but minimal 3D representations.

For real data, we collect street-view video footage from cities spanning all five continents, covering a broad variety of urban environments. The data includes a wide range of viewpoints and motion characteristics, such as static and dynamic captures, first- and third-person perspectives, and varying viewing directions. We segment the videos into short clips to facilitate training.

We automatically generate textual annotations for both real-world videos and full-quality synthetic clips using Tarsier [Yuan et al. 2025], a state-of-the-art video captioning system built on top of the Qwen large multimodal model [Bai et al. 2023]. For each video, we employ a simple and generic prompt (e.g., “Describe the video in detail”), relying on the strong video-language understanding capabilities of Tarsier to produce rich, free-form captions without manual engineering of task-specific prompts.

The resulting captions consistently capture high-level scene context and fine-grained semantic attributes, including human actions



Fig. 13. **Baseline comparison.** We compare our results with a baseline trained with off-the-shelf ControlNet adaptor for Wan2.1. Our model yields more expressive videos, where both humans and scene exhibit more realistic appearance.

and motion patterns, camera motion, clothing appearance, crowd density, weather conditions, environmental layout, architectural style, and location cues derived from the appearance of the city. This process yields expressive and diverse textual descriptions that reflect realistic real-world semantics and visual variability.

We apply this automatic captioning procedure to all real video clips in the dataset as well as to the full-quality synthetic renders. Coarse synthetic videos are not captioned separately; instead, each coarse clip inherits the caption of its corresponding full-quality counterpart. Since both representations are perfectly paired in terms of motion, structure, and scene layout, the caption associated with the realistic render provides an accurate semantic description for the paired coarse input. This design allows the model to learn to condition generation on realistic, high-level textual supervision while operating on minimal and abstract 3D visual representations.

In total, our dataset contains 240K real-world video clips and 1.3K synthetic video clips, each with 5 seconds sampled at 16 fps.

#### A.4 Extra Experiments

**A.4.1 Additional Comparison Examples.** To further evaluate the performance of C2R, we provide an extended qualitative analysis in Figure 13. This figure presents three distinct rows representing the different generation paradigms: our proposed C2R framework, the Wan 2.1 + ControlNet baseline, and standard No-Control T2V (unconditioned text-to-video generation using the Wan 2.1 backbone).

As observed in the top row, C2R effectively translates the coarse input signal into a real urban environment that remains faithful to the prescribed layout and character trajectories. Our model successfully inpaints complex details such as realistic architectural textures, diverse clothing, and dynamic lighting that matches the intended city atmosphere. In contrast, the second row demonstrates that the

Wan 2.1 + ControlNet baseline, while structurally accurate, suffers from a lack of visual diversity. The resulting scenes appear more sterile, with character rendering often appearing less detailed or expressive compared to the C2R outputs.

The final row shows results from No-Control T2V, which represents the raw generative capability of the foundation model without structural conditioning. While these frames achieve a high level of realism and contextual richness, they lack any adherence to the specific camera motion or character trajectories defined by the user. By comparing these three rows, it becomes evident that C2R successfully bridges the gap between the rigid structural adherence of ControlNet and the unconstrained creative expressivity of foundation T2V models. Our framework provides the necessary grounding for simulation workflows while maintaining the high-fidelity aesthetic standards expected of modern generative models.