DiTCtrl: Exploring Attention Control in Multi-Modal Diffusion Transformer for Tuning-Free Multi-Prompt Longer Video Generation

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https://github.com/TencentARC/DiTCtrl

"Athlete on surfboard glides ... across ocean waves ..."

"Athlete on snowboard glides ... across snowy slopes ..."

"Athlete on snowboard glides ... across snowy slopes ..."

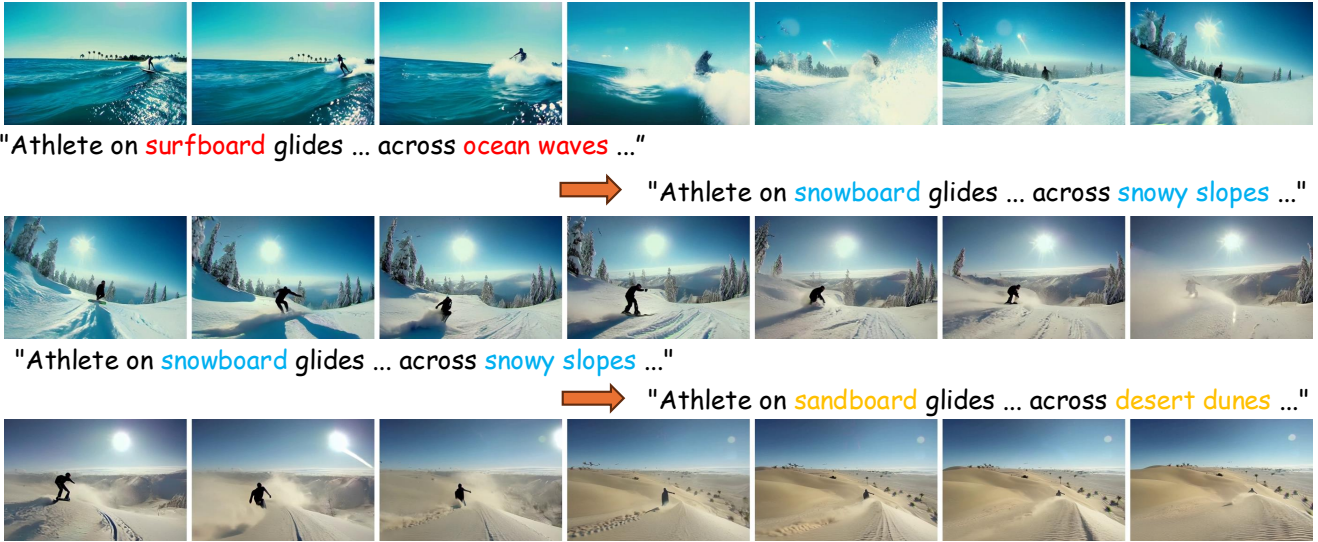"Athlete on sandboard glides ... across desert dunes ..."

Figure 1. The proposed DiTCtrl takes multiple text prompts as input and demonstrates superior capability in generating longer videos with complex motion and smooth transitions as output. In this figure, we showcase a challenging example where an athlete glides through three distinct scenes. Despite the complex subject motion and dramatic camera movement, our method maintains remarkable stability throughout the sequence and seamless semantic transitions that faithfully follow the prompt descriptions.

Abstract

Sora-like video generation models have achieved remarkable progress with a Multi-Modal Diffusion Transformer (MM-DiT) architecture. However, the current video generation models predominantly focus on single-prompt, struggling to generate coherent scenes with multiple sequential prompts that better reflect real-world dynamic scenarios. While some pioneering works have explored multi-prompt video generation, they face significant challenges including strict training data requirements, weak prompt following, and unnatural transitions. To address these problems, we propose DiTCtrl, a training-free multi-prompt video genera-tion method under MM-DiT architectures for the first time. Our key idea is to take the multi-prompt video generation task as temporal video editing with smooth transitions. To achieve this goal, we first analyze MM-DiT's attention mechanism, finding that the 3D full attention behaves similarly to that of the cross/self-attention blocks in the UNet-like diffusion models, enabling mask-guided precise semantic control across different prompts with attention sharing for multi-prompt video generation. Based on our careful design, the video generated by DiTCtrl achieves smooth transitions and consistent object motion given multiple sequential prompts without additional training. Besides, we also present MPVBench, a new benchmark specially designed for multi-prompt video generation to evaluate the performance of multi-prompt generation. Extensive experiments demonstrate that our method achieves state-of-the-art performance

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arXiv:2412.18597v1 [cs.CV] 24 Dec 2024

without additional training.

1. Introduction

Text-to-video (T2V) generation has made remarkable progress in the AIGC era [10, 41, 47], and breakthroughs such as Sora [28] have demonstrated impressive capabilities in generating longer videos through DiT [30] architecture and large-scale per-taining. However, feeding *sequential* prompts into current state-of-the-art video generation models (*e.g.*, Kling [3], Gen3 [2], CogVideoX [45]) fails to produce coherent video sequences that exhibit natural transitions with precise prompt-following. This limitation stems from their fundamental design and single-prompt training paradigm, making them inadequate for depicting real-world scenarios' dynamic, multi-action nature.

Although pioneering works [5, 27, 39] have begun exploring multi-prompt video generation, they face significant challenges. *e.g.*, training such extended video generation models [27, 39] from scratch would require unprecedented computational resources and datasets that are practically unfeasible when the model size increases. Current zero-shot longer video generation methods [21, 33, 40] still mainly focus on the single prompt situation with longer length. Moreover, all previous works [5, 21, 27, 33, 39] are specifically designed under UNet architecture which restricts the abilities of more complex motions and increase the difficulties in multi-prompt generation. However, since Sora 's [28] groundbreaking demonstration of two-minute video generation, highlighting the scalability potential of DiT architectures [30]. Subsequent explorations have led to influential developments, notably in image generation models (Stable Diffusion 3 [13], FLUX.1 [6]) and video generations (CogVideoX [45], Mochi1 [14]). They [6, 13, 14, 45] all adopt a specific kind of DiT architecture, *i.e.*, Multi-Modal Diffusion Transformer (MM-DiT [13]) as the basic unit. This architecture effectively maps text and images (or video) into a unified sequence for attention computation, enabling deeper model scale abilities and achieving superior performances.

Thus, to keep the abilities of the pre-trained single prompt T2V model and take advantage of the performance of the diffusion transformer, we propose DiTCtrl, a *training-free* multi-prompt video generation method under the pre-trained MM-DiT video generation model. Our key observation is that the multi-prompt video generation can be considered a two-step problem: *1) Video editing over time: The new video is generated through the previous video with a new prompt. 2) Video transition over time: Two generated videos need to keep a smooth transition between clips.* Thus, to perform consistent video editing, inspired by the UNet-based image editing techniques [9, 19], we explore the characteristic of the attention modules in the MM-DiT block for the first time,

finding that the 3D full attention has similar behaviors to that of the cross-/self-attention blocks in the UNet-like diffusion models [10, 41]. We thus apply a KV-sharing method between the video clips of different prompts to maintain the semantic consistency of the key objects [9] with the 3D attention control. Besides, we utilize a latent blending strategy for transitions between clips to connect the video clip seamlessly. Finally, to systematically evaluate our method and facilitate future research in multi-prompt video generation, we also introduce MPVBench, a new benchmark with diverse transition types and specialized metrics for assessing multi-prompt transitions. Extensive experiments on this benchmark demonstrate that our method achieves state-of-the-art performance while maintaining computational efficiency.

The contributions of this paper can be summarized as:

- We propose DiTCtrl, the first tuning-free approach based on MM-DiT architecture for coherent multi-prompt video generation. Our method incorporates a novel KV-sharing mechanism and latent blending strategy, enabling seamless transitions between different prompts without additional training.
- We pioneers the analysis of MM-DiT's attention mechanism, finding that 3D full atteniton has similar behaviors to that of the cross/self-attention blocks in the UNet-like diffusion models, enabling mask-guided precise semantic control across different prompts for enhanced generation consistency.
- We introduce MPVBench, a new benchmark specially designed for multi-prompt video generation, featuring diverse transition types and specialized metrics for multi-prompt video evaluation.
- Extensive experiments demonstrate that our method achieves state-of-the-art performance on multi-prompt video generation while maintaining computational efficiency.

2. Related Work

Video Diffusion Model. Diffusion models have achieved significant success in the field of text-to-image generation [26, 34–36], and these advancements have also propelled progress in video generation from text or images [4, 7, 8, 10, 11, 15, 16, 20, 37]. Among these methods, Animate-Diff [16] attempts to turn existing text-to-image diffusion models with a motion module. Other models such as Imagen Video [20] and Make-a-Video [37] train a cascade model of spatial and temporal layers directly in pixel space. To improve efficiency, many other works [4, 7, 8, 10, 11, 15] generate the videos in latent space, leveraging an auto-encoder to compress the video into a compact latent. Notably, most of these text-to-video models utilize a U-Net architecture. Subsequently, the introduction of Sora [28] demonstrates the scalability and advantages of diffusion transformer architecture [30]. Recent works such as CogVideoX [45],

Mochi1 [14], and Movie Gen [31] have adopted the DiT architecture and achieved impressive results. In this work, we build upon the open-source model CogVideoX [45], a DiT-based architecture, to explore attention control mechanisms for multi-prompt long video generation.

Long Video Generation.   Training diffusion models on long videos often demand significant computational resources. Consequently, current video diffusion models are typically trained on videos with a limited number of frames. As a result, the quality of generated videos often degrades significantly during inference when generating longer videos. To address this problem, some works [17, 18, 39, 43] employ an autoregressive mechanism for long video generation. However, due to error accumulation, these methods often suffer from quality degradation after a few iterations. Alternatively, tuning-free methods [5, 21, 33, 38, 40] have been developed to extend off-the-shelf short-video diffusion models for generating long videos without additional training. For instance, Gen-L-Video [40] processes long videos as short video clips with temporal overlapping during the denoising process. FreeNoise [33] explores the influence of initial noises and conducts temporal attention fusion based on the sliding window for temporal consistency. Inspired by these works, we propose a novel KV-sharing mechanism and latent blending strategy for seamless transitions between different segments without additional training.

Image/Video Editing with Attention Control.   Attention control is gaining popularity due to its ability to perform zero-shot image or video editing without the need for additional data. In the realm of image editing, MasaCtrl [9] enhances the existing self-attention mechanism in diffusion models by introducing mutual self-attention. This allows for querying correlated content and textures from source images, ensuring consistent and coherent edits. Prompt-to-Prompt [19] utilizes cross-attention layers to control the relation between text prompts and images, which has also been adopted in many image editing works [12, 29, 44]. When it comes to video editing [22, 23, 32], temporal consistency needs to be considered during attention control. Video-P2P [23] extend the cross-attention control from Prompt-to-Prompt to video editing. FateZero [32] fuses self-attention with a blending mask obtained by cross-attention features from the source prompt. However, all these works are designed for video-to-video translation editing with structure preservation. Differently, we aim for appearance-consistent video editing. Besides, none of these works explore attention control in diffusion transformers. In this paper, we are the first to analyze how the full attention in diffusion transformers could be utilized for editing, similar to U-Net diffusion models.
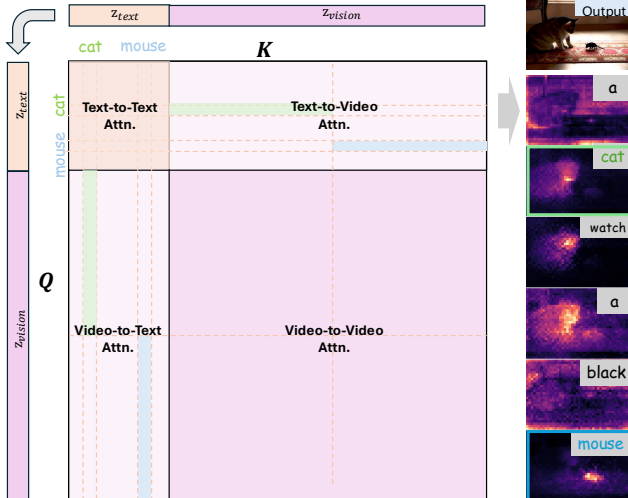

Figure 2. **MM-DiT Attention Analysis**. We find the attention matrix in MM-DiT attention can be divided into four different regions. As for the prompt of *" a cat watch a black mouse"*, each text token shows a high-light response using the average of the text-to-video and video-to-text attention.

3. Method

We tackle the challenge of zero-shot, multi-prompt longer video generation without the need for model training or optimization. This allows us to generate high-quality videos with smooth and precise inter-prompt transitions, covering various transition types (*e.g.*, style, camera movement, and location changes). Formally, given a pre-trained single prompt text-to-video diffusion model $\mathcal{F}$ and a sequence of n prompts $\{P_1, P_2, ..., P_n\}$, the proposed DiTCtrl can generate a coherent longer video $\mathcal{V}_{\{1,...,n\}}$ that faithfully follows these prompts over time, which can be formulated as:

$$\mathcal{V}_{\{1,...,n\}} = \text{DiTCtrl}\{\mathcal{F}(P_1), ..., \mathcal{F}(P_n)\}. \quad (1)$$

Below, we first give a careful analysis of MM-DiT's attention mechanisms (Sec. 3.1). This analysis enables us to design a mask-guided full-attention KV-sharing mechanism for video editing over time (Sec. 3.2) in multi-prompt video generation. Finally, to ensure temporal coherence across different semantic segments, we further incorporate a latent blending strategy that enables smooth transitions in longer videos with multiple prompts (Sec. 3.3).

3.1. MM-DiT Attention Mechanism Analysis

The MM-DiT is the fundamental architecture of the current SOTA method of Text-to-image/Video models [6, 13, 14, 45], which is fundamentally distinct from prior UNet architectures since it maps text and videos into a unified sequence for attention computation. Although it has been widely utilized, the properties of its inner attention mechanism remain insufficiently explored, which restricts its applications in our

multi-prompt longer video generation task. Therefore, for the first time, we conducted a comprehensive analysis of the regional attention patterns in the 3D full attention map based on the state-of-the-art video model, *i.e.* CogVideoX [45].

As shown in Fig. 2, due to the concatenation of the vision and text prompt, each attention matrix can be decomposed into four distinct regions, corresponding to different attention operations: video-to-video attention, text-to-text attention, text-to-video attention, and video-to-text attention. Below, we give the details of each region-inspired previous UNet-like structure with individual attentions [19].

Text-to-Video and Video-to-Text Attention. Previous UNet-like architectures incorporate cross-attention for video-text alignment. In MM-DiT, the text-to-video and video-to-text attention play a similar role. To validate its efficiency, we conduct a detailed analysis of the attention patterns, as illustrated in Fig. 2. Specifically, we compute the averaged attention values across all layers and attention heads, then extract attention values by selecting specific columns or rows corresponding to token indices in both text-to-video and video-to-text regions. These attention values are subsequently reshaped into an $F \times H \times W$ format, allowing us to visualize the semantic activation maps for individual frames. As demonstrated in Fig. 2, these visualizations show remarkable precision in token-level semantic localization, effectively capturing fine-grained relationships between textual descriptions and visual elements. This discovered capability for precise semantic control and localization provides a strong foundation for adapting established image/video editing techniques to enhance the consistency and quality of multi-prompt video generation.

Text-to-Text and Video-to-Video Attention. Text-to-text and video-to-video regional attention are somehow new from the respective UNet structure. As illustrated in Fig. 3, our analysis reveals similar patterns in both components. In the text-to-text attention component (Fig. 3(a)(b), where (a) represents the attention pattern for shorter prompts and (b) illustrates the pattern for longer prompts), we observe a prominent diagonal pattern, indicating that each text token primarily attends to its neighboring tokens. Notably, there are distinct vertical lines that shift backward as the text sequence length increases, suggesting that all tokens maintain significant attention to the special tokens at the end of the text sequence. For the video-to-video attention component, since MMDiT flat the spatial and temporal token for 3D attention calculation, our analysis at the single-frame level reveals a distinctive diagonal pattern in spatial attention (Fig. 3(c)). More significantly, when examining attention maps constructed from tokens at identical spatial positions across different frames, we also observe a pronounced diagonal pattern (Fig. 3(d)). This characteristic mirrors those found in recent UNet-based video models of the spatial-
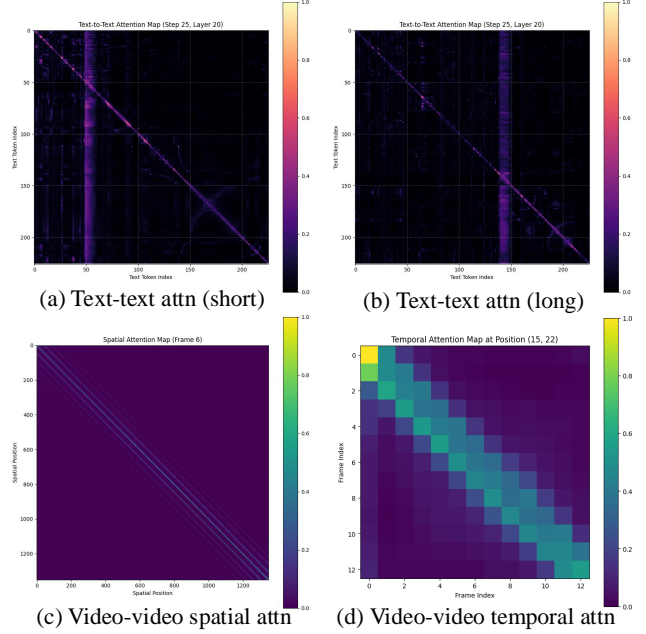

(a) Text-text attn (short)　　(b) Text-text attn (long)

(c) Video-video spatial attn　(d) Video-video temporal attn

Figure 3. **MM-DiT Text-to-Text and Video-to-Video Attention Visualization**. We find that the current MM-DiT has a stronger potential to construct the individual attention in the previous UNet-like structure [10, 11, 41].

attention and temporal attention, such as VideoCrafter [24] and Lavie [42], aligning with the findings reported in [25]. Since previous works only train the specific part of the diffusion model for more advanced control and generation, our finding provides strong evidence for these methods from MM-DiT perspectives.

Overall, the presence of these consistent diagonal patterns in the MM-DiT architecture demonstrates robust frame-to-frame correlations, which proves essential for maintaining spatial-temporal coherence and preserving motion fidelity throughout the video sequence.

3.2. Consistent Video Generation Over Time

Based on the previous analysis, we find the attention mechanism in the MM-DiT has a similar behavior as that in the UNet-like video diffusion model with our specific design. Thus, we propose the masked-guided KV-sharing strategy for consistent video generation over time for our multi-prompt video generation task.

Specifically, as shown in Fig. 4, to generate the consistent video between prompt P_{i-1} and prompt P_i, we utilize the intermediate attentions from the $i-1$-th and i-th prompt in MM-DiT to generate the attention mask of the specific consistent object, respectively. This is achieved by averaging all the text-to-video/video-to-text parts of the 3D full attention with the given specific subject token. With these masks, we then perform mask-guided attention fusion to generate the
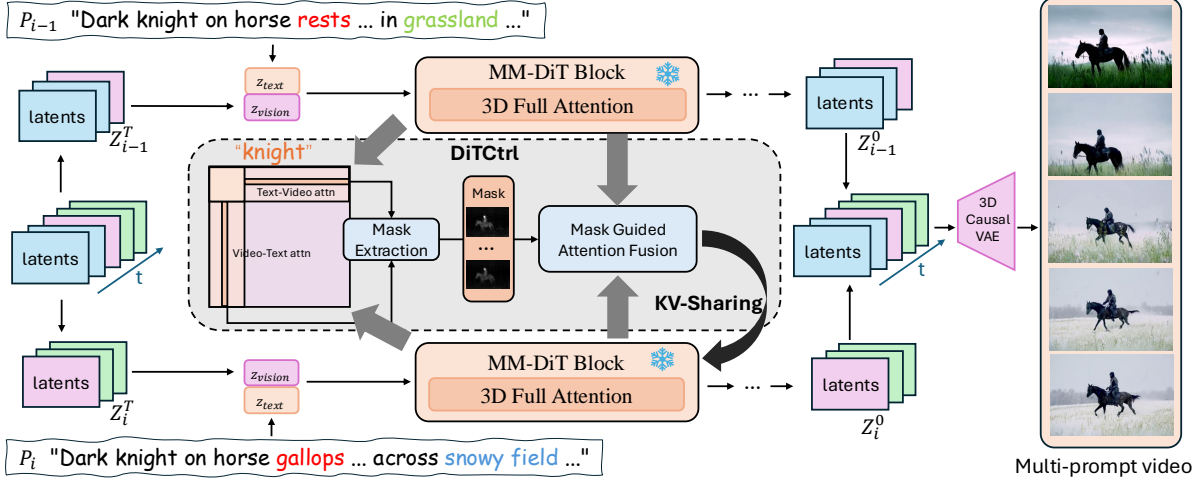
Figure 4. **Pipeline of the proposed DiTCtrl**. Our method tries to synthesize content-consistent and motion-consistent videos based on multi-prompts. The first video is synthesized with source text prompt P_{i-1}. During the denoising process for video synthesis, we convert the full-attention into masked-guided KV-sharing strategy to query video contents from source video $\mathcal{V}_{i-1}$, so that we can synthesize content-consistent video under the modified target prompt P_i. Note that initial latents are assumed to be 5 frames. The first three frames are used to generate the contents of P_{i-1}, and the last three frames are used to generate contents of P_i. The pink latent represents the overlapping frame, while the blue and green latents are used to distinguish different prompt segments.

new attention features of the prompt P_i. Inspired by MasaCtrl [9], we directly utilize the key and values from the prompt P_{i-1} to guide the generation of prompt P_i to generate the consistent appearance over time.

Formally, at step t, we perform a forward pass with the fixed MM-DiT backbone with prompt P_{i-1} and next prompt P_i, respectively, to generate intermediate regional cross-attention maps. Then we average the attention maps across all heads and layers with the same spatial resolution $H \times W$ and temporal frames F. The resulting cross-attention maps are denoted as $A_i^c \in \mathbb{R}^{F \times H \times W \times N}$, where N is the number of the textual tokens. We then obtain the averaged cross-attention map for the token correlated to the foreground object. We denote M_{i-1} and M_i as masks extracted for the foreground objects in $\mathcal{V}_{i-1}$ and $\mathcal{V}_i$, respectively. With these masks, we can restrict the object in $\mathcal{V}_i$ to query contents information only from the object region in $\mathcal{V}_{i-1}$:

$$f_o^l = \text{Attention}(Q_i^l, K_{i-1}^l, V_{i-1}^l; M_{i-1}), \quad (2)$$

$$f_b^l = \text{Attention}(Q_i^l, K_{i-1}^l, V_{i-1}^l; 1 - M_{i-1}), \quad (3)$$

$$\bar{f}^l = f_o^l * M_i + f_b^l * (1 - M_i), \quad (4)$$

where $\bar{f}^l$ is the final attention output. Then, we replace the feature map of the current step to f_o^l for further calculation.

3.3. Latent Blending Strategy for Transition

While our previous methods enable semantic consistency between clips, achieving smooth transitions between different semantic segments still needs to be carefully designed. Thus, we propose a latent blending strategy to ensure temporal

coherence across different semantic segments, inspired by recent works in single-prompt long video generation [33, 46].

As illustrated in Fig. 5, our approach introduces overlapped regions between adjacent semantic video segments (video $\mathcal{V}_{i-1}$ and video $\mathcal{V}_i$). For each frame position in the overlapped region, we apply a position-dependent weight function that follows a symmetric distribution - frames closer to their respective segments receive higher weights while those at the boundaries receive lower weights. This weighting scheme ensures smooth transitions between different semantic contexts.

Formally, given two adjacent video segments $\mathcal{V}_{i-1}$ and $\mathcal{V}_i$ generated from prompts P_{i-1} and P_i respectively, we propose a latent blending strategy as follows. Let T denote the number of overlapped frames between segments. For frame position t in the overlapped region, we compute its blended latent features $\mathbf{z}_t$ as:

$$\mathbf{z}_t = w(t) \cdot \mathbf{z}_{t,i-1} + (1 - w(t)) \cdot \mathbf{z}_{t,i}, \quad (5)$$

where $\mathbf{z}_{t,i-1}$ and $\mathbf{z}_{t,i}$ are latent features from $\mathcal{V}_{i-1}$ and $\mathcal{V}_i$ respectively, and $w(t)$ is a position-dependent triangular weight function defined as:

$$w(t) = \min\left(\frac{2(t+0.5)}{T}, 2 - \frac{2(t+0.5)}{T}\right), \quad t \in [0, T-1] \quad (6)$$

The key advantage of our approach is that it requires no additional training while effectively handling transitions between different semantic contexts. During each denoising
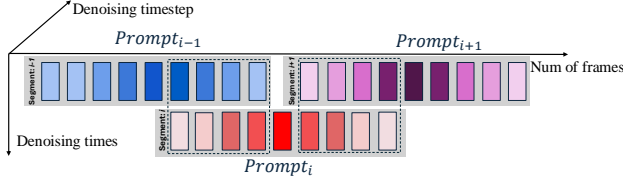
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Figure 5. **Latent blending strategy** for video transition between video clips.

step, we first process each segment independently, then progressively blend the latent features in the overlapped regions using position-dependent weights. This strategy maintains temporal coherence while smoothly transitioning between different semantic contexts, making it particularly suitable for multi-prompt video generation tasks.

4. Experiments

We implement DiTCtrl based on CogVideoX-2B [45], which is a state-of-the-art open-source text-to-video diffusion model based on MM-DiT. In our experiments, we generate multi-prompt conditioned video, and each video clip consists of 49 frames with 480×720 resolution. Moreover, we employ ChatGPT [1], to generate multiple transitions of different types. We set latent sampling frames and overlap sizes to 13 and 6 in our experiments. The experiments are conducted on a single NVIDIA A100 GPU.

4.1. Qualitative Results

We conduct comprehensive qualitative comparisons with state-of-the-art multi-prompt video generation methods [33, 38, 40] and leading commercial solutions [3]. To ensure a fair comparison, we additionally implement FreeNoise [33] on the CogVideoX backbone as an enhanced baseline.

As shown in Fig. 6, our proposed method demonstrates superior performance across three critical aspects: text-to-video alignment, temporal coherence, and motion quality. While Kling [3] exhibits impressive capabilities in high-quality video generation, it is limited to simultaneous multi-semantic blending rather than sequential semantic transitions, highlighting the significance of our work in achieving temporally evolving content across multiple prompts.

Our comparative analysis reveals distinct characteristics and limitations of existing approaches. Gen-L-Video [40] suffers from severe temporal jittering and occasional subject disappearance, compromising overall video quality. Video-Infinity [38] and FreeNoise [33] both demonstrate successful scene-level semantic changes but lack physically plausible motion - for instance, in Fig. 6, vehicles appear to be in motion while remaining spatially fixed, which is a limitation inherent to their UNet-based abilities. In contrast, FreeNoise+DiT leverages the DiT architecture's abilities to achieve more realistic object motion but struggles with semantic transitions, resulting in noticeable discontinuities

between segments. Our proposed DiTCtrl method preserves the inherent capabilities of the pre-trained DiT model while addressing these limitations, enabling smooth semantic transitions and maintaining motion coherence throughout the video sequence. For a more comprehensive evaluation, we provide additional frame-level and video-level comparisons with extensive qualitative examples in the supp.

4.2. Quantitative Results

In this section, we will first elaborate on our proposed new benchmark MPVBench for evaluating multi-prompt video generation, and then discuss the quantitative results.

MPVBench. MPVBench contains a diverse prompt dataset and a new metric customized for multi-prompt generation. Specifically, leveraging GPT-4, we produce 130 long-form prompts of 10 different transition modes. Then, for multi-prompt video generation, we observe that the distribution of the CLIP features differs between single-prompt and multi-prompt scenarios. As shown in Fig. 7, the feature points of natural video follow a continuous curve, while those of two concatenated isolated videos follow two continuous curves with a breakpoint in the middle. Since the common CLIP similarity calculates the average of neighborhood similarities, the difference between natural and isolated video only occurs at the breakpoint, which becomes very small when divided by the number of frames. To address this limitation, we propose *CSCV* (Clip Similarity Coefficient of Variation), a metric specifically designed to evaluate the smoothness of multi-prompt transitions, defined as:

$$s_i = \mathbf{x}_i^\top \mathbf{x}_{i+1}, \quad i = 1, \ldots, n-1 \tag{7}$$

$$\text{score} = \frac{1}{1 + \lambda \cdot \frac{\sigma(s)}{\mu(s)}}, \tag{8}$$

where $\mathbf{x}_i$ denotes frame features, σ and μ are standard deviation and average respectively. The Coefficient of Variation $CV = \sigma(s)/\mu(s)$ describes the degree of uniformity, which can largely punish the isolated situation. The function $\frac{1}{1+\lambda(\cdot)}$ projects the score to $[0, 1]$, the larger the better.

Automatic Evaluation. We conduct the automatic evaluation with our MPVBench. From Table 1 one can see that our method achieves the highest CSCV score, demonstrating superior transition handling and overall stability in generation patterns. While FreeNoise ranks second with relatively strong stability, other methods significantly lag behind in this aspect, which is consistent with the T-SNE visualization of CLIP embedding as shown in Fig. 7. In terms of motion smoothness, our approach exhibits superior performance in motion quality and consistency. Regarding Text-Image Similarity metrics, although FreeNoise and Video-Infinity achieve higher scores, this can be attributed to our method's kv-sharing mechanism, where subsequent video segments inherently learn from preceding semantic content.

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"A SUV drives on a dirt road ...sunny ... " ➡️ "A SUV drives on a snow road ...thick clouds ... "

Figure 6. Generation results on given prompts by our method and baseline models. Kling is the commercial model, and Freenoise+DiT is our implementation of Freenoise on CogVideoX.
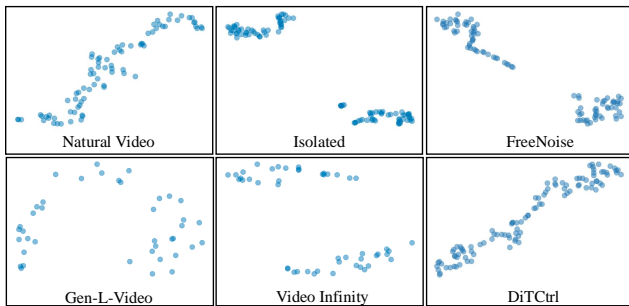

Figure 7. **T-SNE visualization of CLIP embeddings**. Each point represents the CLIP embedding of a single video frame after dimensionality reduction. The visualization demonstrates that conventional multi-prompt videos form distinct clusters, while our method produces a more continuous distribution, indicating smoother semantic transitions.

Method	CSCV	Motion smoothness	Text-Image similarity
Gen-L-Video	59.44%	83.36%	30.58%
FreeNoise	84.37%	97.22%	**32.69%**
FreeNoise+DiT	78.74%	97.76%	30.90%
Video-Infinity	74.97%	97.31%	32.35%
DiTCtrl(w/o kv-sharing)	81.79%	97.35%	31.37%
DiTCtrl(Ours)	**84.90%**	**97.80%**	30.68%

Table 1. **Evaluation metrics.** Comparison of performance metrics for various video generation methods as benchmarked by MPVBench. Bold values represent the best performance within each group.

As shown in Fig. 6, our design choice allows the road surface to gradually transition to snowy conditions while retaining features from the previous scene. Despite potentially lower text-image alignment scores, it ensures superior semantic continuity in the sequences. In practice, this trade-off doesn't negatively impact the visual quality in multi-prompt scenarios, as demonstrated by our user study results presented below.

Human Evaluation. We invited 28 users to evaluate five models: Gen-L-Video [40], Video-Infinity [38], FreeNoise [33], FreeNoise+DiT and our method. We employ a Likert scale ranging from 1 (low quality) to 5 (high quality). Participants score each method considering overall preference, motion pattern, temporal consistency and

text alignment over 16 videos generated by different scenarios. As clearly indicated in Table 2, generated videos from our method significantly outperform other state-of-the-art approaches in all four criteria, demonstrating superior capability in producing videos with natural semantic transitions that better align with human preferences for visual coherence and continuity. More details will be provided in the supplementary material.

4.3. Ablation Study

We conducted ablation studies to validate the effectiveness of DiTCtrl's key components: latent blending strategy, KV-sharing mechanism, and mask-guided generation as shown in Fig. 8. The first row shows results that directly using text-to-video models results in abrupt scene changes and disconnected motion patterns, failing to maintain continuity in the athlete's movements from surfing to skiing. The second row demonstrates that DiTCtrl without the latent blending strategy achieves basic video editing capabilities
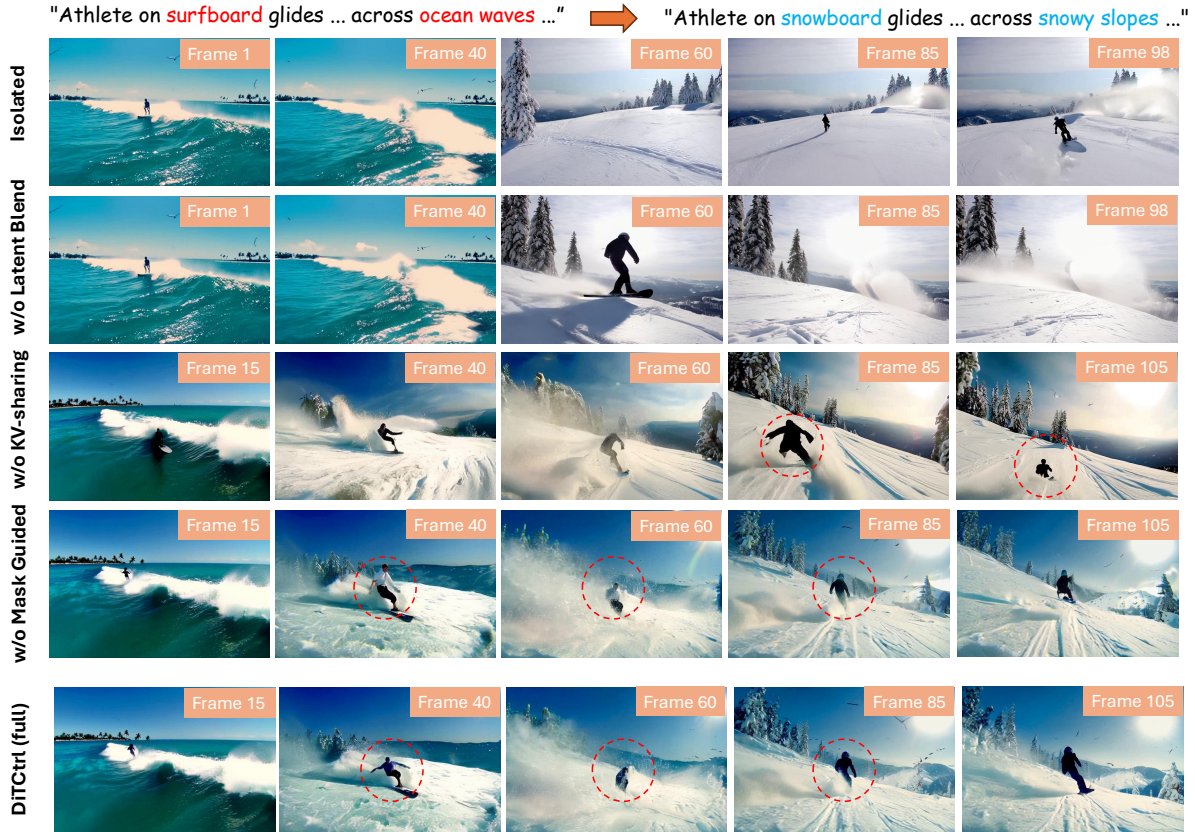
Figure 8. **Ablation Component in DiTCtrl**. The first and second rows have 98 frames, while the remaining methods generate 105 frames.

Method	Overall preference	Motion Pattern	Temporal Consistency	Text Alignment
Gen-L-Video	1.15	1.14	1.08	1.25
FreeNoise	3.02	2.90	2.99	3.08
FreeNoise+DiT	3.81	3.93	3.75	3.78
Video-Infinity	2.90	2.85	2.91	2.98
DiTCtrl(Ours)	**4.11**	**4.17**	**4.26**	**3.91**

Table 2. **User study**. Human evaluation of different video generation methods across multiple aspects. Scores range from 1 to 5, with higher scores indicating better performance. Bold values represent the best performance within each metric.

Figure 9. **single prompt longer video generation example.**

but lacks smooth transitions between scenes. Without KV-sharing (third row), DiTCtrl exhibits unstable environmental transitions and significant motion artifacts, with inconsistent character scaling and deformed movements. Moreover, DiTCtrl without mask guidance (fourth row) improves motion coherence and transitions but struggles with object attribute confusion across different prompts and environments. On the other hand, The full DiTCtrl implementation provides the most precise control over generated content, demonstrating superior object consistency and smoother transitions between prompts while maintaining desired motion patterns. These results validate our analysis of MM-DiT's attention mechanism and its role in enabling accurate semantic control.

4.4. More Applications

Single-prompt Longer Video Generation.

Our method can naturally work on single-prompt longer video generation. As illustrated in Fig. 9, using the prompt "A white SUV drives on a steep dirt road", our approach successfully generates videos that are more than 12 times longer than the original length, while maintaining consistent motion patterns and environmental coherence.

Video Editing. We show how we use our methods to achieve video editing performance (*e.g.* "reweight" and "word swap"). The cases are provided in the Appendix. C.

5. Conclusion

In this paper, we introduce DiTCtrl, a novel, tuning-free method for multi-prompt video generation using the MM-DiT architecture. Our pioneering analysis of MM-DiT's attention mechanism reveals similarities with the cross/self-attention blocks in UNet-like diffusion models, enabling mask-guided semantic control across prompts. With KV-sharing mechanisms and latent blending strategies, DiTCtrl ensures smooth transitions and consistent object motion between semantic segments, without extra training. We also present MPVBench, the first extensive evaluation framework for multi-prompt video generation, set to advance future research in this field.

Limitation & Future Work. While our method demonstrates state-of-the-art performance, there remain two primary limitations. First, compared to image generation models, current open-source video generation models exhibit relatively weaker conceptual composition capabilities, occasionally resulting in attribute binding errors across different semantic segments. Second, the computational overhead of DiT-based architectures presents challenges for inference speed. These limitations suggest promising directions for future research in enhancing semantic understanding and architectural efficiency.

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Overview

This supplementary material presents comprehensive experimental details, qualitative analyses, and technical implementations of our work. We provide extensive evaluations across multiple aspects, including baseline comparisons, diverse application scenarios, and ablation studies. Note that our project page shows many cases of our results, comparison and diverse application scenarios. The content is organized into five main sections:

- Section A details our experimental framework, including baseline implementations, evaluation metrics, and human evaluation protocols.
- Section B showcases comprehensive qualitative results across diverse domains, featuring detailed comparisons with state-of-the-art models and demonstrating the versatility of our approach.
- Section C explores various applications, including single-prompt video generation and advanced editing capabilities such as attention reweighting and word swap techniques.
- Section D presents the usage of *prompt generator*, including full descriptions used to generate individual prompts.
- Section E presents comprehensive ablation studies, including both quantitative evaluations and qualitative analyses of the masking mechanism.

A. Implementation Details

Details. We implement DiTCtrl based on CogVideoX-2B [45], which is a state-of-the-art open-source text-to-video diffusion model based on MM-DiT. The hyperparameters and implementation details are shown in Tab. 3.

Table 3. Hyperparameters of DiTCtrl.

Hyperparameters	
base model	CogVideoX-2B
sampler	VPSDEDPMPP2MSampler
sample step	50
guidance scale	6
resolution	480×720
sampling num frames	13
overlap size	6
kv-sharing steps	[2,25]
kv-sharing layers	[25,30]
threshold	0.3
λ of CSCV	10

Baselines. To demonstrate the effectiveness of our proposed DiTCtrl, we conduct comprehensive qualitative comparisons with state-of-the-art multi-prompt video generation methods [33, 38, 40] and leading commercial solutions Kling [3]. Both FreeNoise and Video-Infinity are built upon

the VideoCrafter2 [11] framework. To ensure a fair comparison of base models, we implement FreeNoise [33] as an enhanced baseline by directly incorporating their noise rescheduling strategy into the CogVideoX framework.

MPVBench. We introduces a new benchmark MPVBench, which is specified designed for multi-prompt video generation task. MPVBench contains a diverse prompt dataset and a new metric customized for multi-prompt generation. Specifically, leveraging GPT-4, we produce 130 long-form prompts of 10 different transition modes (background transition, subject transition, camera transition, style transition, lighting transition, location transition, speed transition, emotion transition, clothing transition, action transition). The instruction of prompt generator is provided in Fig. 19.

Automatic evaluation. For automatic evaluation, we generate videos using 130 prompts from our MPVBench, with three random seeds set. Then, we evaluate the generated video by three metrics: CSCV (Clip Similarity Coefficient of Variation), Motion Smoothness, Text-Image Similarity.

Human evaluation. In our user study, we combined our generated videos with those produced by four other baseline methods. We asked a total of 28 participants to evaluate the videos across four dimensions: overall preference, motion pattern, temporal consistency, and text alignment. Specifically, we asked all participants to rank the results of these methods for each of the following questions, and assigned a score from 1 (lowest quality) to 5 (highest quality) for these five methods:

- **Overall Preference**: "*Please rank the overall video preference.*" This metric evaluates participants' comprehensive assessment of the generated videos.
- **Motion Pattern**: "*How natural and realistic are the motion in the video?*" This evaluates whether the motion of objects in the generated video appears physically plausible and natural, such as whether vehicles drive realistically, animals move naturally, or human actions appear authentic.
- **Temporal Consistency**: "*How smoothly does the video content transition across different frames?*" This metric evaluates the temporal coherence of the generated video, focusing on whether the transitions between consecutive frames are natural and continuous, without abrupt changes or visual artifacts. It measures the video's ability to maintain visual continuity throughout its duration.
- **Text Alignment**: "*To what extent does the video content match the given text descriptions?*" This assesses the semantic fidelity between the generated visual content and the input text prompts, examining whether the video accurately captures and visualizes the key elements and actions described in the prompts. It measures how well the visual narrative aligns with the intended textual description.

Mask-guided Implementation Details. We show how mask extracted from MM-DiT attention map is utilized for mask-
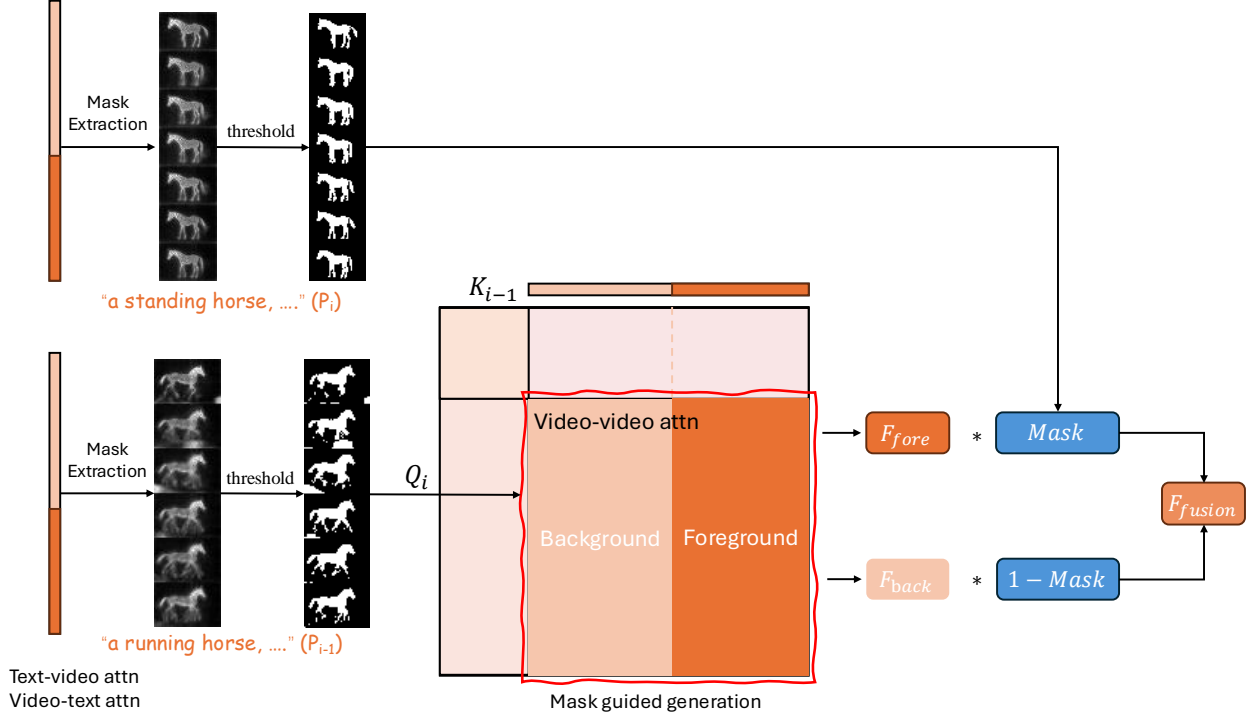
Figure 10. Mask-guided KV-sharing details.

guided KV-sharing strategy in Fig. 10, to generate consistent video over time for multi-prompt video generation task.

Specifically, Fig. 10 illustrates our approach to generating temporally consistent videos in multi-prompt video generation tasks. When computing attention for the P_i branch latent, we utilize attention maps from both P_{i-1} and P_i branches. Specifically, we extract content from the Text-video and Video-text attention regions of their attention maps. By focusing on specified tokens (e.g., "a running horse"), we obtain and average the corresponding regional values to generate semantic mask maps. These maps are then binarized through thresholding to create foreground-background segmentation masks M_{i-1} and M_i.

Then, we leverage M_{i-1} to guide the computation of KV-sharing attention maps (calculating attention between Q_i and K_{i-1}, V_{i-1}), resulting in foreground-focused attention outputs F_{fore} and F_{back}. The final fusion is achieved through M_i as follows:
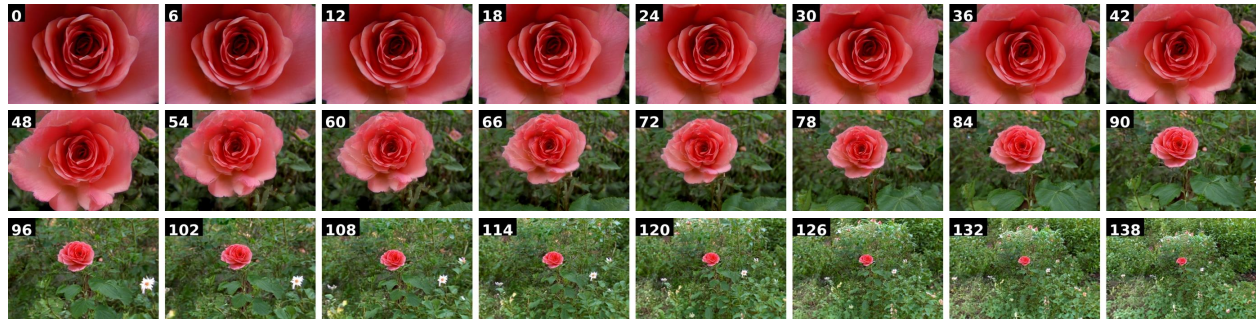
$$F_{fusion} = F_{fore} * M_i + F_{back} * (1 - M_i) \qquad (9)$$

This mask-guided approach ensures semantic consistency while maintaining smooth transitions between different prompts.

B. More Qualitative Results

More results are provided in Fig. 11 and Fig. 12. Our method DiTCtrl can generate multi-prompt videos with good tem-
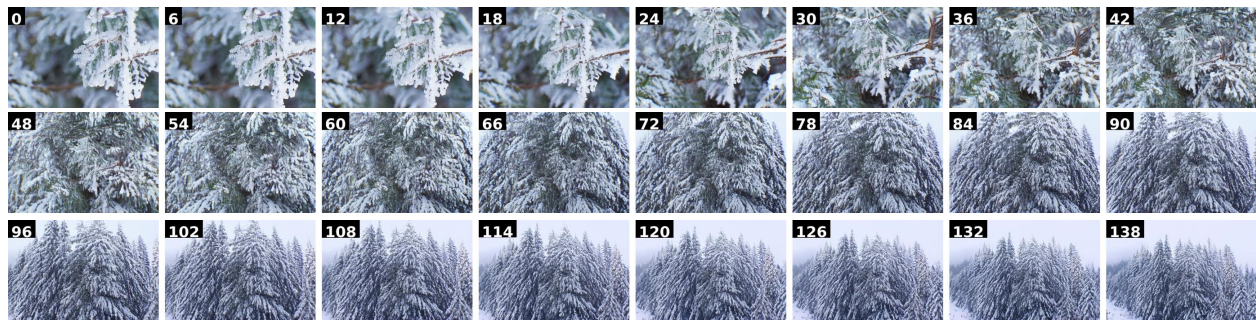
poral consistency and strong prompt-following capabilities, demonstrating cinematographic-style transitions in depicting the boy's riding sequence. We also give more qualitative comparisons with state-of-the-art multi-prompt video generation methods [33, 38, 40], our reproduced FreeNoise+DiT, and leading commercial solutions Kling [3]. We show the *motion transition* case, and *background transition* case in Fig. 13 and Fig. 14. Our comparative analysis reveals distinct characteristics and limitations of existing approaches. Gen-L-Video [40] suffers from severe temporal jittering and occasional subject disappearance, compromising overall video quality. Video-Infinity [38] and FreeNoise [33] both demonstrate successful scene-level semantic changes but lack physically plausible motion - for instance, in Fig. 13, dark knight appear to be in motion while remaining spatially fixed, which is a limitation inherent to their UNet-based abilities. In contrast, FreeNoise+DiT leverages the DiT architecture's abilities to achieve more realistic object motion but struggles with semantic transitions, resulting in noticeable discontinuities between segments. Our proposed DiTCtrl method preserves the inherent capabilities of the pre-trained DiT model while addressing these limitations, enabling smooth semantic transitions and maintaining motion coherence throughout the video sequence. More comparison of visualization case and our results are shown in our project page.

(a) "**Close-up shot → medium shot → wide shot** of a blooming rose, cinematic"

(b) "Boy cycling **through corridor → to doors → into garden**, cinematic, 4K"

(c) "Frosty pine: **close-up shot → medium shot → forest vista**, cinematic"

Figure 11. More multi-prompt results

C. Applications

Based on our exhaustive analysis and exploration of attention control in MM-DiT architecture, our method could be applied to other tasks like single prompt longer video generation and video editing and achieves promising results.
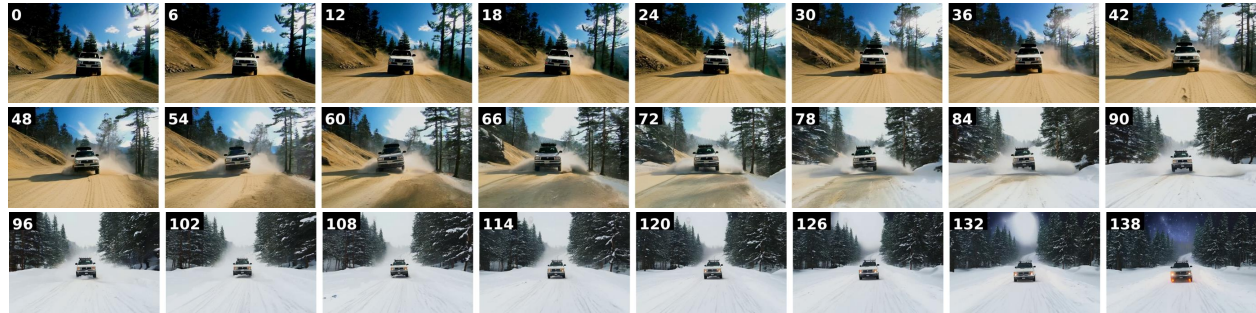
C.1. Single-prompt Longer Video Generation

Although our primary objective is to address multi-prompt video generation, we discover that our method demonstrates remarkable effectiveness in single-prompt longer video generation as well. Our method can naturally work on single-prompt longer video generation. As illustrated in Fig. 15, our approach successfully generates longer videos, while maintaining consistent motion patterns and environmental coherence.

C.2. Video Editing

In this work, we conduct an in-depth analysis of MM-DiT's attention maps, which can be categorized into four components: Text-to-Video and Video-to-Text Attention, Text-to-Text and Video-to-Video Attention. Through our analysis of Text-to-Video and Video-to-Text Attention, we observe that semantic maps can be obtained by specifying token indices, suggesting potential for semantic control. We have emphasized the use of extracted foreground-background segmentation semantic maps to guide video generation, effectively preventing semantic confusion between foreground and background elements. In this section, we demonstrate video editing capabilities through two approaches: *Reweight* and *Word Swap*.
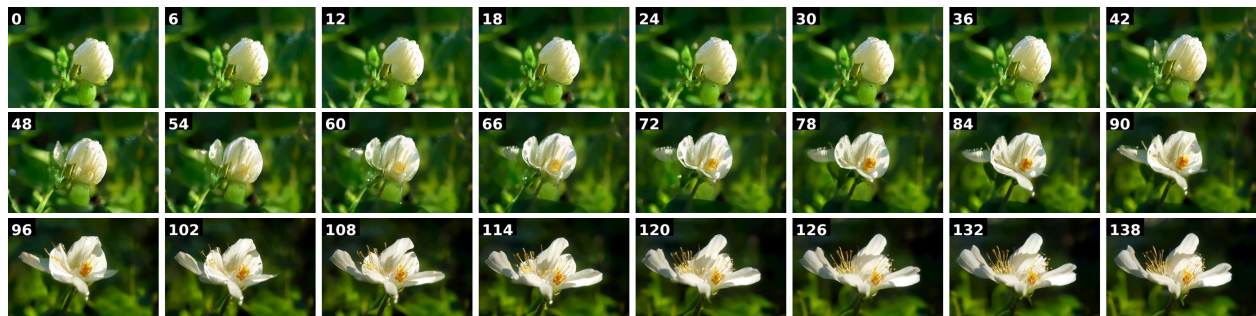
Attention Re-weighting. As illustrated in Fig. 16, we can

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(a) "A white SUV driving on **dirt road → snowy path → starry night**"

(b) "Dark knight **rests in grassland → gallops across snowy fields → desert**"

(c) "A flower **bud emerges → unfolds gracefully → stands in full bloom**"

Figure 12. More multi-prompt results

achieve semantic enhancement or attenuation by increasing or decreasing the values in rows or columns corresponding to token j in the Text-to-Video and Video-to-Text Attention maps. In Fig. 16 (a), we demonstrate semantic attenuation by reducing Text-Video Attention values in the row and Video-Text Attention values in the column corresponding to "pink". In Fig. 16 (b), we achieve semantic enhancement by increasing Text-Video Attention values in the row and Video-Text Attention values in the column corresponding to "snowy". These results validate the semantic control capabilities of Text-Video and Video-Text Attention in MM-DiT.

Word Swap. Building upon the concept introduced in Prompt-to-prompt [19], this approach allows users to swap tokens in the original prompt with alternatives (e.g., changing P ="a large bear" to "a large lion"). The primary challenge lies in maintaining the original composition while accurately

reflecting the content of the modified prompt. Our DiTCtrl method incorporates KV-sharing, similar to the word swap mechanism in [19], where we share key-value pairs from the previous prompt to compute the corresponding video for the subsequent prompt across selected layers and steps. Specifically, DiTCtrl (without latent-blending strategy) enables token-replacement video editing while ensuring consistency in other content elements, as demonstrated in Fig. 17. This implementation validates the feasibility of prompt-to-prompt-style video editing within the MM-DiT architecture.

D. Prompt Generator

We use GPT4 for longer multi-prompt generation, our prompts are shown in Fig. 19. This figure shows the generation process of "background transition", and we generate

Figure 13. Motion and background transition.

Figure 14. Background transition.

10 different transition modes (background transition, subject transition, camera transition, style transition, lighting transition, location transition, speed transition, emotion transition, clothing transition, action transition). The detailed prompts will be provided in the the *prompts.txt* in the attached supplementary.

E. Ablation Study

E.1. Quantitative Results of Components

As shown in Tab. 4, our latent blending strategy (second row) demonstrates superior video consistency compared to iso-lated clips (first row), as evidenced by higher CSCV scores - our proposed metric for evaluating multi-prompt transition smoothness. Furthermore, our KV-Sharing mechanism further improves the CSCV value, achieving enhanced stability. The mask-guided approach(fourth row) and its unmasked counterpart(third row) report comparable scores, suggesting that the contribution of masking foreground object to overall frame transition smoothness is modest. However, our quali-tative analysis in Section E.2 reveals that the mask-guided method yields superior visual results.

Additionally, in our evaluation of motion smoothness, our full method (DiTCtrl) achieves optimal performance. Re-
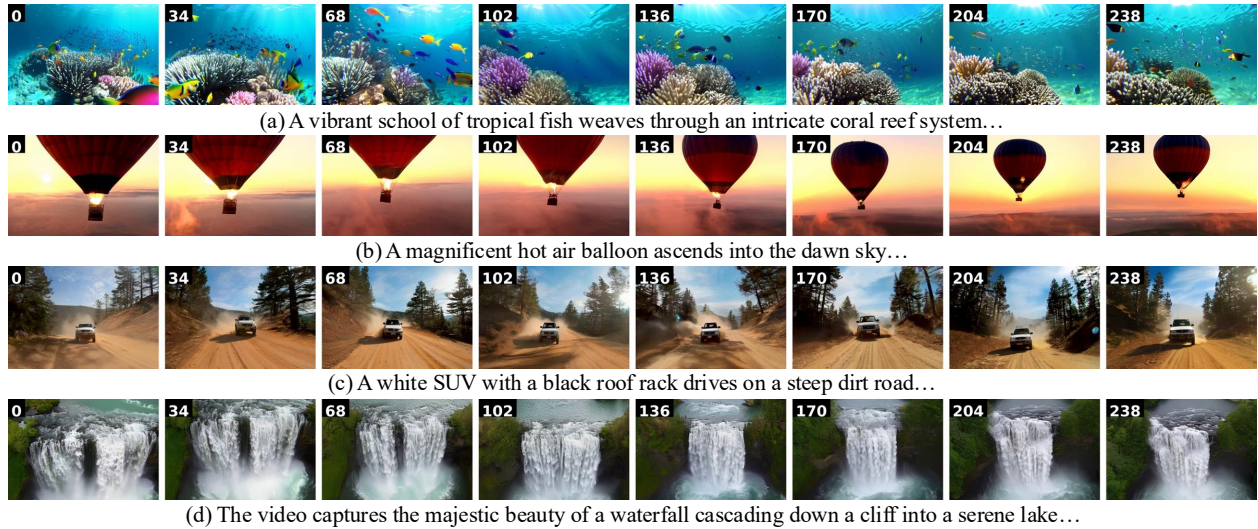
(a) A vibrant school of tropical fish weaves through an intricate coral reef system…

(b) A magnificent hot air balloon ascends into the dawn sky…

(c) A white SUV with a black roof rack drives on a steep dirt road…

(d) The video captures the majestic beauty of a waterfall cascading down a cliff into a serene lake…

Figure 15. Visualization of single prompt longer video generation.

Pink (↓) teddy bear wearing a cute pink bow tie

(a) Weaken token - *pink*

A video of a house on a snowy (↑) mountain
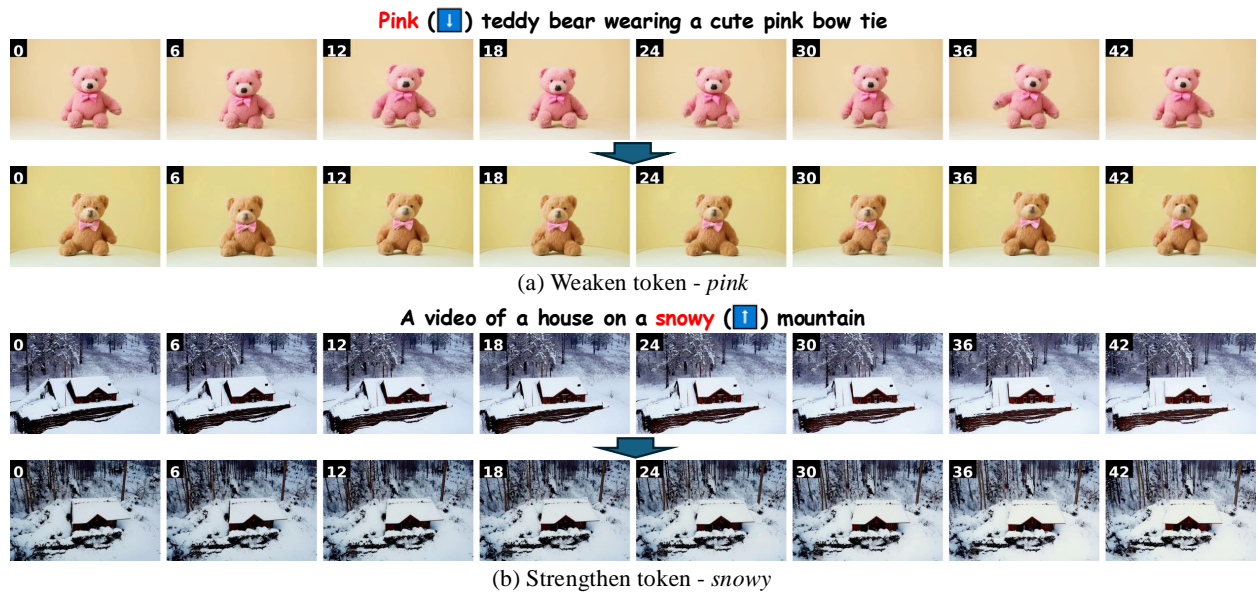

(b) Strengthen token - *snowy*

Figure 16. Reweighting example of Video Editing.

garding the Text-Image similarity metric, we observe a slight expected decrease with our approach. This is attributable to our methodology where the latent representation of latter video segments incorporates Keys and Values from preceding segments to maintain consistency. This inherently introduces semantic information from previous segments, marginally reducing the current segment's alignment with its corresponding text prompt. However, this trade-off is justified as our method achieves stable transitions and effectively conveys both semantic elements, resulting in higher user study scores as shown in Tab. 2.

Method	CSCV	Motion smoothness	Text-Image similarity
Isolated	72.37%	97.78%	**32.05%**
DiTCtrl(w/o kv-sharing)	81.79%	97.35%	31.37%
DiTCtrl(w/o mask-guided)	**84.92%**	97.76%	30.66%
DiTCtrl(full)	84.90%	**97.80%**	30.68%

Table 4. Comparison of metrics for ablation.

E.2. Mask-guided Generation Analysis

We present comparative results in Fig. 18 to demonstrate the effectiveness of our mask-guided KV-sharing strategy. In Fig. 18 (a), while the first prompt describes a single horse, the second prompt emphasizes a zebra leading its herd. With-
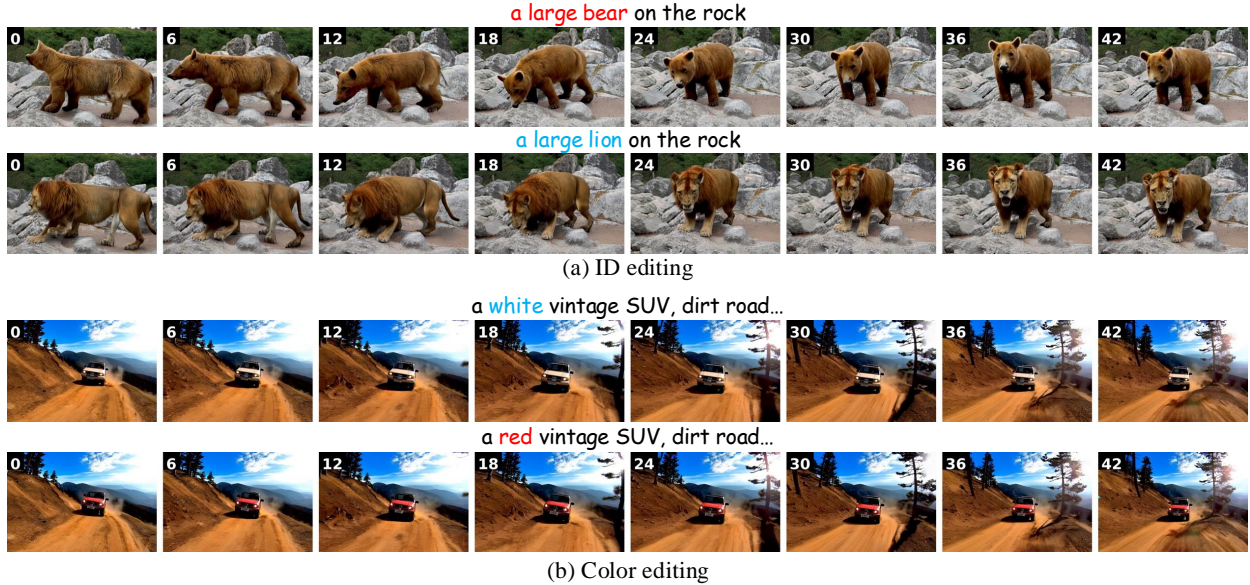
17

a large bear on the rock

a large lion on the rock

(a) ID editing

a white vintage SUV, dirt road...

a red vintage SUV, dirt road...

(b) Color editing

Figure 17. Word Swap example of Video Editing.

w/o mask

w mask

(a) ID transition: horse to zebra

w/o mask

w mask

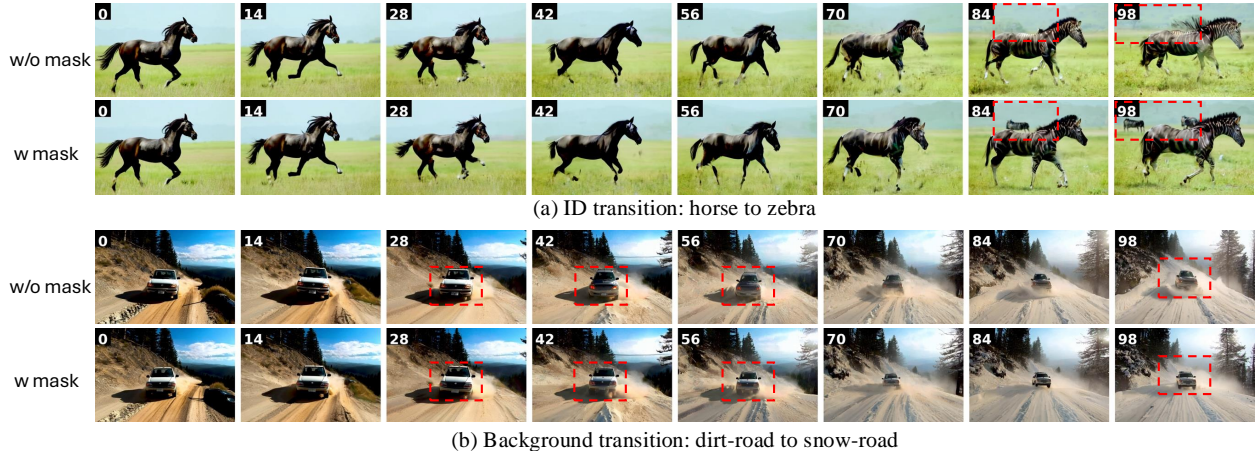(b) Background transition: dirt-road to snow-road

Figure 18. Ablation study of mask-guided KV-sharing results. First row shows our model without mask-guided KV-sharing, while the second row demonstrates our full model with mask-guided KV-sharing. The prompt for (a) transitions from "A powerful horse gallops across a field..." to "A striking zebra leads its herd across the field...". The prompt for (b) evolves from "A white SUV drives a dirt road..." to "A white SUV powers through snow..."

out mask-guided KV-sharing (first row), we observe that the model fails to properly generate the zebra herd and exhibits background inconsistencies. In contrast, our full model with mask-guided KV-sharing (second row) successfully maintains scene coherence while incorporating the herd elements.

Similarly, in Fig. 18 (b), the transition sequence in the first row (without mask-guided KV-sharing) shows notable deformations in the vehicle's appearance, including undesired color variations. The second row, implementing our mask-guided approach, better preserves the vehicle's original appearance, color, and shape throughout the transition. These results validate both the effectiveness of our mask-guided approach and the feasibility of leveraging semantic maps extracted from MM-DiT's Text-Video and Video-Text

Attention for application in Video-Video Attention.

You are part of a team of bots that creates multi-prompt videos. You work with an assistant bot that will draw anything you say in square brackets.

For example , outputting "a beautiful morning in the woods with the sun peaking through the trees" will trigger your partner bot to output an video of a forest morning , as described. You will assist people to create detailed, amazing videos by generating prompt groups. These grouped prompts are used to generate a single scenario, controlling the video content progression over time to create multi-prompt videos. Therefore, these prompts should not differ too much. The way to accomplish this is to first generate short prompts according to a given category, and then, extend them. When you extend the prompts, you should always keep them similar.

1. Taking two prompts in a group for example. There are some instances for generating short prompts:
Given the category "Background transition":
" A jeep car is running on the beach, sunny.;\
A jeep car is running on the beach, night. "
You can see the generated short prompts only differ a little. And the sentences have no logic relation. Therefore, words like "the same" in the prompts are prohibited.

2. There are some rules for extending the prompts:

• Please give me prompts that are exactly same but can highlight the core differences in description.
• When modifications are requested , you should not simply make the description longer . You should refactor the entire description to integrate the suggestions.
• Video descriptions should have similar number of words as examples below. Maximum words of one prompt are 226.

Here are some examples. You should generate prompts with similar number of words as below:
"A dark knight rests motionless atop a majestic black horse in the middle of a vast grassland. The rider's armor gleams dully in the diffused light, while tall grass sways gently in the breeze. The overcast sky creates a moody atmosphere as the horse and rider remain still, surveying the expansive landscape that stretches to the horizon.;\
   A dark knight guides the majestic black horse at a steady gallop across a snow-covered field. The rider's armor contrasts sharply against the white landscape, while snowflakes swirl in their wake. The overcast sky and blanket of snow create a stark winter atmosphere as the horse and rider move purposefully through the pristine terrain.;\
   A dark knight guides the majestic black horse at a steady gallop across the vast desert expanse. The rider's armor shimmers brilliantly in the harsh sunlight, while sand particles dance in their wake. The blazing sky and endless dunes create a scorching atmosphere as the horse and rider move purposefully through the sun-baked terrain.;"

Let us start! The first category is "Background transition". For 2-prompt group, 3-prompt group, 4-prompt group and 5-prompt group, first generate 13 groups of short prompts and then extend them. Give me BOTH the short prompt groups, and the extended ones.

Figure 19. Our instruction to create multiple individual long prompts based on short prompts group of specified types