Generative Video Propagation

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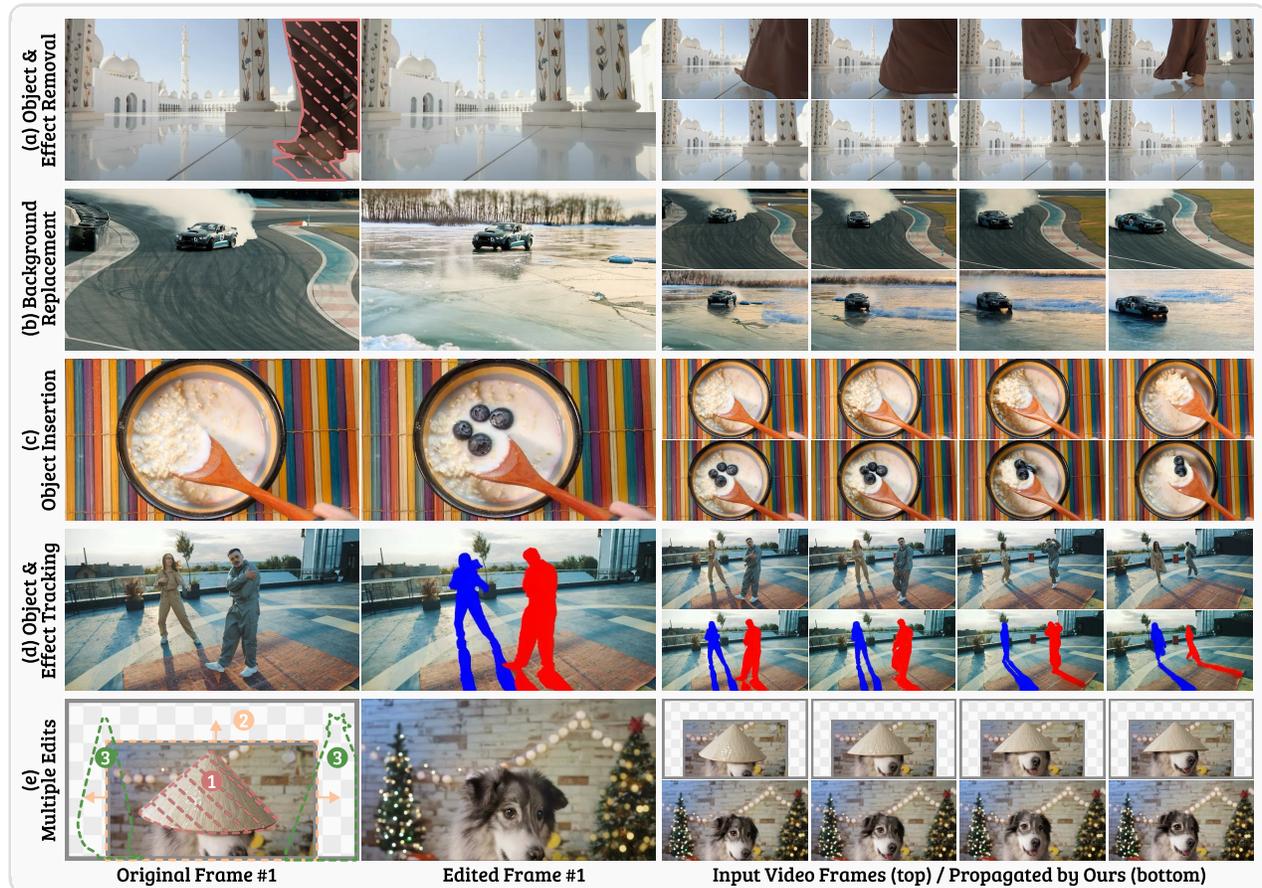* Work done during an internship at Adobe. † Co-corresponding authors.

Figure 1. GenProp. We propose a generative video propagation framework (GenProp), which can seamlessly propagate any first frame edit through the video. GenProp supports a wide range of video applications, including (a) complete object removal with effects such as shadows and reflections, (b) background replacement with realistic effects, (c) object insertion where inserted objects have physically plausible motion (i.e., blueberries falling while spoon goes up), (d) tracking of objects and their associated effects, and (e) multiple edits (outpainting, insertion, removal) at a single inference run.

Abstract

*Large-scale video generation models have the inherent ability to realistically model natural scenes. In this paper, we demonstrate that through a careful design of a **generative video propagation framework**, various video tasks can be addressed in a unified way by leveraging the generative power of such models. Specifically, our framework, Gen-Prop, encodes the original video with a selective content encoder and propagates the changes made to the first frame using an image-to-video generation model. We propose a data generation scheme to cover multiple video tasks based on instance-level video segmentation datasets. Our model is trained by incorporating a mask prediction decoder head*

and optimizing a region-aware loss to aid the encoder to preserve the original content while the generation model propagates the modified region. This novel design opens up new possibilities: In editing scenarios, GenProp allows substantial changes to an object's shape; for insertion, the inserted objects can exhibit independent motion; for removal, GenProp effectively removes effects like shadows and reflections from the whole video; for tracking, GenProp is capable of tracking objects and their associated effects together. Experiment results demonstrate the leading performance of our model in various video tasks, and we further provide in-depth analyses of the proposed framework.

1. Introduction

Recently, large-scale video generation models [7, 17, 18, 32, 35, 42, 46, 57] have shown impressive performance, generating highly realistic videos while being able to simulate the complexities of the real world. In this rapidly evolving domain, following works in video generation have extended the text-to-video (T2V) generation to image-to-video (I2V) [2, 5, 32, 53, 60], and are further exploring various video editing tasks such as video inpainting [65], appearance editing [34, 43], object insertion [31], usually focusing on that specific task. In this paper, we bring a new perspective, observing that many of such video applications can be modeled as a general *video propagation* problem.

Video propagation itself is not a new concept, with traditional methods often relying on optical flow [9, 44], depth [6, 55], radiance fields [33], and atlases [20, 24] to propagate the changes in sparse intermediate frames (typically the first frame) to the rest of the video. However, such approaches can be prone to error accumulation, leading to limited robustness and generalization ability. Furthermore, they often focus on a single task [9, 33] or entail retraining for a specific task for propagation [28, 31, 34, 61]. In contrast, we extend the first-frame editing and design a more general framework for *generative video propagation* encompassing various editing scenarios by leveraging video generation models's power in modeling real-world scenes.

Our model, *GenProp*, is able to propagate the changes in the first frame to the whole video while keeping other parts consistent to the original video, without requiring any additional motion predictions (e.g., optical flow). This general formulation enables many downstream applications such as removal, insertion, replacement (object and/or background), text-based editing, outpainting and even object tracking, some of which are shown in Fig. 1. We further demonstrate that our model is also able to *expand* the scope of what is usually achievable in each task, specifically: (1) substantial shape modifications in object editing tasks, (2) independent motion of inserted objects in insertion tasks, (3) removal of object effects like shadows and reflections
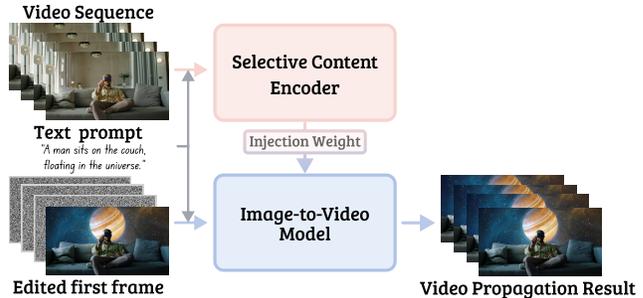

Figure 2. Model Overview. During inference, our framework takes in the original video as input through a selective content encoder (SCE) to retain content in unchanged regions. Changes applied to the first frame are propagated throughout the video using an I2V model while other regions remain intact.

in removal tasks, and (4) accurate tracking of objects along with their associated effects. Note that unlike existing video editing models that often require a dense mask labeling for all individual frames (e.g., for object removal), GenProp does not require any mask input, thanks to the propagation-based approach, greatly simplifying the editing process.

Our model architecture consists of two main components as shown in Fig. 2: the Selective Content Encoder (SCE) that encodes the information of the original video, and the I2V generation model that takes in the edited first frame for propagation. The training objective is to allow SCE to selectively encode the features of the unchanged parts of the video, while preserving the generation capabilities of I2V models to propagate the altered parts. To effectively disentangle these two functions, we introduce a region-aware loss and penalize the gradients within the modified region for SCE, as ideally, SCE should not encode content in the edited area. For training the model, we propose using synthetic data derived from video instance segmentation datasets. As shown in the attention map visualizations in Fig 3, we observe that GenProp indeed attends to the region to be modified and the I2V model is guided to generate (propagate) the new content into those regions. To further aid the model, we incorporate an auxiliary decoder head during training to predict the modified region.

Our contributions are summarized as follows:
- We extend first-frame editing to a general *generative video propagation* framework, which propagates changes in the first frame to the entire video using the generative power of I2V models, enabling broader applications.
- We carefully design our model, *GenProp*, with a Selective Content Encoder (SCE), dedicated loss functions and a mask prediction head and propose a synthetic data generation pipeline for training this model.
- Our model supports various downstream applications such as removal, insertion, replacement, editing, and tracking. We observe that it supports outpainting, with-

out task-specific data during training.
- Experiment results show that our model outperforms SOTA methods in video editing and object removal while expanding the scope of existing tasks including tracking.

2. Related Work

Video Propagation. Traditional methods are typically designed for a single task and often require retraining for new tasks [9, 21, 33]. Many approaches address propagation by first tracking instance masks, then performing inpainting [25, 26], with segmentation often as the initial step. SAM 2 [39], the current SotA tracking model, can track the masks accurately and efficiently. Some methods rely on optical flow [9, 44] or depth [6, 55] to ensure consistent motion and spatial coherence. CoDef [33] uses deformation fields from the source video to guide edits from the first frame. While these representations aid motion tracking and structural consistency, they add complexity and may limit flexibility, especially with significant shape changes or complex backgrounds. Depth, sketches, and optical flow can also be combined with diffusion models [11, 29, 48, 52, 56].

Diffusion-based Video Editing. Most diffusion-based video editing methods rely on text control, where the primary goal is to make edits that are coherent to text prompts while preserving the unchanged regions of the video. Some methods utilize text-to-image models for zero-shot editing through attention control [6, 14, 23, 37, 41, 47, 49]. Some other works require intermediate variables like optical flows or depth maps to stabilize motion. Others rely on per-case fine-tuning to adapt to specific motion [4, 30, 50, 62], but this approach is typically slow and prone to generate similar results from the original video due to reconstruction tuning. SORA [32] denoises the noised videos under the target description to do editing. These methods are generally limited to altering the appearance rather than making significant changes to object shapes. Additionally, because of unclear attention maps, especially in complex scenes, background changes often lack precision and coherence. InsV2V [8] and EVE [43] edit videos based on text instructions but are also limited to appearance changes. Some recent efforts have attempted to directly edit motion based on text prompts [22, 58, 63], but their resulting video output tends to strike a balance between the text-based guidance and the original video's motion, which can be hard to control.

Image-to-Video Generation and Editing. Image-to-video (I2V) generation models take an input image along with a text prompt to generate a sequence of frames, making them a foundational application in video generation due to its familiarity and versatility. Notable open-source models include Stable Video Diffusion [5], I2VgenXL [60], and SparseCtrl [16], while high-performance commercial models, such as Gen-2, PikaLabs [2], SORA [32], and Movie
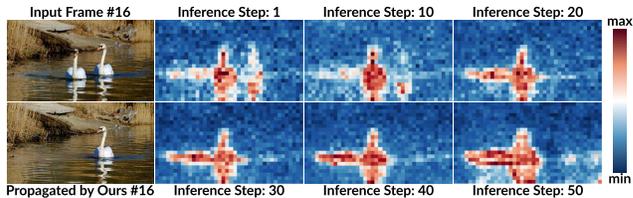

Figure 3. Attention Map Visualization. We observe that the attention maps gradually focus on the regions to be removed and the I2V model is guided to generate new content in those regions.

Gen [35], further push the boundaries in this field.

Several methods propagate edits from the first frame. For example, some works [13, 40, 55, 56] rely on first-frame edits but require auxiliary inputs like optical flow or depth maps for motion continuity. VideoSwap [15] uses sparse key points to control the motion. AnyV2V [27] and VideoShop [12] can also propagate first-frame edits across a video sequence; however, as a training-free framework, its generalization ability is limited. I2VEdit [34], in contrast, necessitates learning motion LoRAs [19] for each video clip, adding computational complexity. Revideo [31], built on Stable Video Diffusion (SVD), enables control over the generation using the edited first frame and a specified motion trajectory. However, its approach involves masking parts of the input video with a black square, which removes significant information and restricts the method in handling complex background edits and large shape alterations.

3. Method

Generative video propagation has the following key challenges: (1) Realism – changes in the first frame should be naturally propagated to the following frames, (2) Consistency – all other regions should remain consistent to the original video, and (3) Generality – the model should be general enough to be applicable to multiple video tasks. In GenProp, we leverage an I2V generation model for (1); we introduce a selective content encoder and a mask prediction decoder and train the model with a region-aware loss to address (2); and we propose a data generation scheme and also benefit from the versatile I2V model for (3).

3.1. Problem Formulation

Given an input video $V = \{v_1, v_2, \ldots, v_T\}$ with T frames, let v_1' denote the modified first frame. The goal is to propagate this modification, producing a modified video $V' = \{v_1', v_2', \ldots, v_T'\}$, where each frame v_t' (for $t = 2, \ldots, T$) retains the modification applied to the key frame v_1 while maintaining consistency in both appearance and motion throughout the sequence. We employ a latent diffusion model that encodes pixel information in the latent space. With a slight abuse of notations, we continue using v_t for this latent representation. In formal terms, during inference,
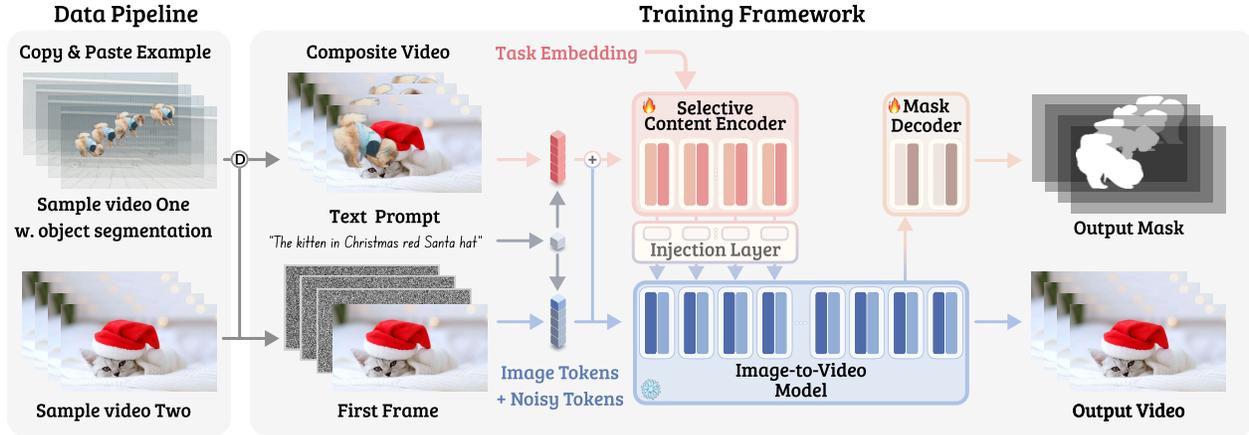
Figure 4. Training Framework of GenProp. Our framework integrates a Selective Content Encoder and a Mask Prediction Decoder on top of the I2V generation model, enforcing the model to propagate the edited region while preserving the content in the original video for all other regions. With synthetic data augmentations and task embeddings, our model is trained to propagate various changes in the first frame.

GenProp generates each frame v'_t as:

$$v'_t = \mathcal{G}(\mathcal{E}(V), v'_1, t), \quad \forall t \in \{2, \ldots, T\}, \qquad (1)$$

where $\mathcal{G}$ is the I2V generation model guided by the selective content encoder (SCE), $\mathcal{E}(V)$.

For training, we use synthetic data constructed from existing video instance segmentation datasets to create paired samples (details given in Sec. 3.4). We define a data generation operator $\mathcal{D}$ that constructs training data pairs $(v_i, \hat{v}_i)$ from an original video sequence V. Let $\mathcal{D}(V)$ denote the synthetic data generation operator applied to the original video sequence, where:

$$(v_i, \hat{v}_i) \in \mathcal{D}(V), \quad \forall i \in \{1, \ldots, T\}. \qquad (2)$$

Then $\hat{V} = \{\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_T\}$ is the synthetic video sequence. GenProp is trained to satisfy the following objective across all frames $i \in \{2, \ldots, T\}$:

$$\min_{\mathcal{E}} \sum_{i=2}^{T} \mathcal{L}(\mathcal{G}(\mathcal{E}(\hat{V}), v_1, i), v_i) \qquad (3)$$

where $\mathcal{L}$ is a region-aware loss designed to disentangle the modified and unmodified regions, enforcing stability in the unchanged areas while allowing for accurate propagation in the edited regions (details in Sec. 3.3). To ensure that the final output adheres to real video data distributions, synthetic data is fed exclusively to the content encoder. The I2V generation model, however, uses the original video, preventing the model from inadvertently learning synthetic artifacts.

3.2. Model Design

To preserve the unchanged parts of the original video and only propagate the modified regions, we integrate two additional components to the base I2V model: Selective Content Encoder and Mask Prediction Decoder, as shown in Fig. 4.

Selective Content Encoder. The architecture of our SCE is a replicated version of the initial N blocks of the main generation model, similar to ControlNet [59]. After each encoder block, the extracted features are added to the corresponding features in the I2V model, allowing a smooth and hierarchical flow of content information. The injection layer is one multilayer perceptron with zero initialization which will also be trained. Furthermore, for bidirectional information exchange, the features of the I2V model are fused with the SCE's input before the first block. This lets SCE be aware of the modified regions so that it can selectively encode the information in the unchanged region as intended.

Mask Prediction Decoder. The Mask Prediction Decoder (MPD) is designed to estimate the spatial regions requiring editing, helping the encoder disentangle changes from the unchanged content. While SCE utilizes the initial N blocks of the I2V model, MPD mirrors this by using the final block along with one multilayer perceptron (MLP) as the final layer. It takes the latent representation from the penultimate block, which contains rich spatial and temporal information, and processes it through the MLP layer. This restores the temporal dimension, matching it to the number of video frames. The final output is trained to match the instance mask of the video via an MSE loss [10] $\mathcal{L}_{\text{MPD}}$. This guides the model to focus on the edited regions and significantly improves the accuracy of the attention maps.

3.3. Region-Aware Loss

In our training process, we use instance segmentation data to ensure that both the edited and unedited regions receive appropriate supervision. We design a Region-Aware Loss (RA Loss), shown in Fig. 5, to balance the loss of both regions, even when the edited areas are proportionally small.

For an input video $\hat{V} = \{\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_T\}$ and instance-
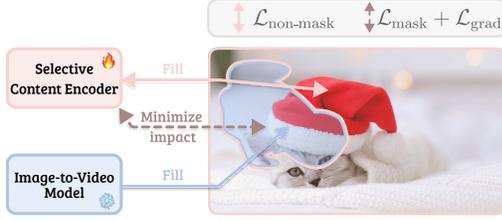
Figure 5. Region-Aware Loss. This loss helps the model to disentangle the edited region from the original content.

level masks $M = \{m_1, m_2, \ldots, m_T\}$, where $m_t \in \{0, 1\}^{H \times W}$ indicates edited regions in frame $\hat{v}_t$, we apply Gaussian downsampling over the spatial dimensions and repeat over the temporal dimension to obtain a mask $\tilde{m}_t$ that is aligned to the shape of the latent representation of the video. The loss is separately computed for the mask and non-mask region, giving:

$$\mathcal{L}_{\text{mask}} = \mathbb{E}_{t \sim \mathcal{U}(1,T)} \left[\mathcal{L}_{\text{d}}(\tilde{m}_t \cdot v_t^{\text{out}}, \tilde{m}_t \cdot v_t) \right] \text{ and} \quad (4)$$

$$\mathcal{L}_{\text{non-mask}} = \mathbb{E}_{t \sim \mathcal{U}(1,T)} \left[\mathcal{L}_{\text{d}}((1 - \tilde{m}_t) \cdot v_t^{\text{out}}, (1 - \tilde{m}_t) \cdot v_t) \right],$$

where $\mathcal{L}_{\text{d}}$ denotes the diffusion MSE loss that measures the pixel-wise error between the generated frame v_t^{out} and ground truth v_t.

To further reduce the SCE's influence on the masked regions, we add a gradient loss $\mathcal{L}_{\text{grad}}$ that minimizes the effect of the masked area in the encoder's input. Instead of computing second-order gradients, we approximate using a finite difference:

$$\Delta f = \frac{f(\mathcal{E}(\hat{V} + \delta)) - f(\mathcal{E}(\hat{V}))}{\delta} \quad (5)$$

where $f(\mathcal{E}(\hat{V}))$ represents the encoder's feature, and δ is a small perturbation. The gradient loss is defined as:

$$\mathcal{L}_{\text{grad}} = \mathbb{E}_{t \sim \mathcal{U}(1,T)} \left[\tilde{m}_t \cdot \|\Delta f\|_2 \right]. \quad (6)$$

The RA Loss $\mathcal{L}$ is a weighted sum of all three terms to ensure sufficient supervision on both masked and unmasked areas:

$$\mathcal{L} = \mathcal{L}_{\text{non-mask}} + \lambda \cdot \mathcal{L}_{\text{mask}} + \beta \cdot \mathcal{L}_{\text{grad}} + \gamma \cdot \mathcal{L}_{\text{MPD}} \quad (7)$$

3.4. Synthetic Data Generation

Creating a large-scale paired video dataset can be costly and challenging especially for video propagation, as it is difficult to encompass all video tasks. To address this, we propose to use synthetic data derived from video instance segmentation datasets. In our training, we use Youtube-VOS [54], SAM-V2 [39], and an internal dataset. However, this data generation pipeline can be applied to any available video instance segmentation dataset. Specifically, we adopt

a mix of augmentation techniques to the segmentation data, tailored to various propagation sub-tasks: (1) *Copy-and-Paste*: Objects from one video are randomly segmented and pasted into another, simulating object insertion; (2) *Mask-and-Fill*: The masked region undergoes inpainting, creating realistic edits within selected regions; (3) *Color Fill*: The masked area is filled with specific colors, representing basic object tracking scenarios. For (3), V will be sent to $\mathcal{E}$ and $\hat{v}_1$ will be sent to $\mathcal{G}$ in Eq. 3. Each synthetic data type aligns with a distinct task, enabling our model to generalize across diverse applications. Task embeddings corresponding to these augmentation methods are injected into the model, guiding the model to adapt based on the augmentation type. Note that despite the variety of data creation methods and tasks, the core function of SCE remains consistent: encode the unedited information while the I2V model maintains the generative capabilities to propagate the edited regions. More details about each augmentation technique are provided in the Supplementary Material.

4. Experiments

4.1. Implementation Details

As GenProp is a general framework, we experiment with both a DiT architecture similar to Sora [32] and a U-Net architecture based on Stable Video Diffusion (SVD) [5] as the base video generation model. For the former, it is trained for I2V generation on 32, 64, and 128 frames at 12 and 24 FPS, with a base resolution of 360p. SCE (24 blocks) and MPD are trained while the I2V model is frozen. The results can be upscaled to 720p using a super-resolution model. The learning rate is set to 5e-5 with a cosine-decay scheduler and a linear warmup. An exponential moving average is applied for training stability. A gradient norm threshold of 0.001 prevents training instability. Classifier-free guidance (CFG) value is set to 20, and the data augmentation ratio is set to 0.5/0.375/0.125 for copy-and-paste/mask-and-fill/color fill. In the RA loss, λ is 2.0, β is 1.0, and γ is 1.0. All experiments were conducted on 32/64 NVIDIA A100 GPUs for different architectures. We find that the DiT backbone has a better video generation quality. Our main results are from this DiT variant while the ablation studies are conducted with the SVD-based architecture. Please refer to the Supplementary Material for the results based on SVD.

4.2. Comparisons

As generative video propagation is a new problem, we compare the SotA methods in each of the three sub-tasks of GenProp. Note that our model is able to handle these tasks within the same model and further cover additional tasks such as outpainting as well as combinations of these sub-tasks as shown in the bottom row of Fig. 1. We provide extensive results in the Supplementary Material.

Figure 6. Visual Comparison in Multiple Video Tasks. GenProp demonstrates versatile editing capabilities, (a) allowing seamless modification of objects into those with vastly different shapes with independent motion and (b) enabling background edits. For object removal, GenProp excels at (c) effectively removing object effects together with the object and (d) realistically reconstructing large occluded areas. It is further able to perform instance tracking of objects and their effects when solid color fills are given as the first frame (see (e)).

Diffusion-based Video Editing In Fig. 6 (a) and (b), we compare GenProp with other diffusion-based video editing methods, including text-guided and image-guided approaches. InsV2V [8] relies on instruction text for controlling generation. However, due to its limited training data, it struggles with significant shape changes and does not support object insertion. Pika [2] also uses text prompts to edit within a box region, but it performs poorly when the object's shape changes substantially and cannot handle background edits or object insertion. AnyV2V [27]

Method	Classic Test Set					Challenging Test Set				
	$PSNR_m$ ↑	CLIP-T ↑	CLIP-I ↑	GenProp preference % Alignment	Quality	$PSNR_m$ ↑	CLIP-T ↑	CLIP-I ↑	GenProp Preference % Alignment	Quality
InsV2V [8]	28.999	0.3049	0.9737	60.00	60.00	28.842	0.2906	0.9718	81.82	75.00
AnyV2V [27]	32.090	0.3050	0.9676	95.56	86.67	28.338	0.3302	0.9576	97.78	95.56
Pika [2]	32.568	0.3226	**0.9923**	62.22	55.56	31.329	0.3023	0.9886	88.89	86.67
ReVideo [31]	31.765	0.3196	0.9777	75.56	71.11	29.920	0.3226	0.9798	84.44	82.22
GenProp (Ours)	**33.837**	**0.3229**	0.9825	-	-	**32.163**	**0.3336**	**0.9904**	-	-

Table 1. Video editing benchmark compared to existing models. $PSNR_m$ measures the consistency outside the edited region. CLIP-T and CLIP-I measure text alignment and frame consistency. User study shows the percentage of users who preferred Ours over the compared method on alignment (left) and quality (right). GenProp significantly outperforms the other methods on the Challenging Set.

Method	CLIP-I ↑	GenProp Preference % Alignment	Quality
SAM + Propainter	0.9809	82.22	75.56
ReVideo [31]	0.9728	86.36	77.27
GenProp (Ours)	**0.9879**	-	-

Table 2. Object removal comparison to other methods. GenProp outperforms baselines on consistency, alignment, and quality.

Method	CLIP-T ↑	CLIP-I ↑
w/o MPD	0.3252	0.9834
w/o RA Loss	0.3261	0.9825
GenProp (Ours)	**0.3316**	**0.9872**

Table 3. Ablation study. Both MPD and RA loss can improve the success rate of editing and the quality of the output video.

is a training-free method that uses the first frame to guide editing. While it handles appearance changes, it fails when there are large shape or background modifications, often resulting in degradation or ghosting effects. Like InsV2V and Pika, it also cannot insert objects. We use ReVideo [31] to manage large shape changes by first removing an object and then re-inserting it, but this two-stage process has drawbacks. The box-based region can cause blurry boundaries, and object motion is affected by the original point tracking, leading to accumulated errors. Additionally, the box region limits its ability to edit complex backgrounds effectively.

Video Object Removal For object removal, we compare GenProp with a traditional inpainting pipeline, where we cascade two SotA models to achieve a propagation-like inpainting, since traditional methods require a dense mask annotation for all frames: SAM-V2 [39] for mask tracking, then Propainter [64] for inpainting the regions in the estimated masks. As shown in Fig. 6 (c) and (d), GenProp has several advantages: (1) no need for a dense mask annotation as input; (2) removal of object effects like reflections and shadows; (3) removal of large objects and natural filling within large areas.

Video Object Tracking We compare GenProp with SAM-V2 [39] on tracking performance in Fig. 6 (e). Since SAM-V2 is trained on the large-scale SA-V dataset, it is expected that SAM-V2 often produces more precise tracking masks than GenProp. Additionally, GenProp is slower than real-time tracking methods like SAM-V2. However, it has notable advantages. Due to its video generation pretraining, GenProp has a strong understanding of physical rules. As shown in Fig. 6, unlike SAM-V2, which struggles with ob-

ject effects like reflections and shadows due to limited and biased training data, GenProp can consistently track these effects. This highlights the potential of approaching classic vision tasks with generation-based models.

Quantitative Results We conduct a quantitative evaluation on several test sets. For video editing (reported in Tab. 1), we evaluate on two types of test sets: (1) Classic Test Set, which is TGVE [51]'s DAVIS [36] part and its "Object Change Caption" as the text prompt, focusing on object replacement and appearance editing; (2) Challenging Test Set, which is 30 manually collected videos from Pexels [1] and Adobe Stock [3] including large object replacement, object insertion and background replacement. For (2), the first frame is edited using a commercial photo editing tool. For Pika [2], we use the online boxing tool, running it three times for each result. For ReVideo [31], we select a box region, then to track appearance changes, we use its code to extract the original object's motion points. For edits with significant shape changes, we first remove the original object and then insert the new object, assigning a future trajectory. For assessing the consistency in the unchanged regions, we measure the PSNR outside the edit mask, denoted as $PSNR_m$. For cases with large shape changes, we apply a rough mask over the original and edited regions, only calculating the PSNR on areas outside these masks. For text alignment, we compute the cosine similarity between the CLIP [38] embeddings of the edited frame and the text prompt (CLIP-T) [31, 34, 51]. For consistency, we calculate the distance between CLIP [38] features across frames (CLIP-I) [31, 34, 51]. As shown in Tab. 1, GenProp outperforms the other methods on most metrics, especially on the Challenging Test Set. Pika exhibits better consis-
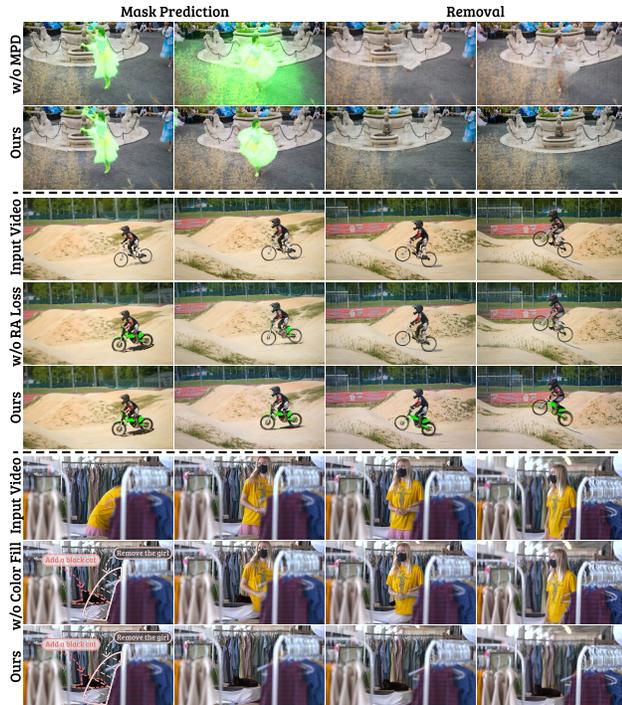
Figure 7. Visual comparison of model variants, showing the effect of MPD training (top), RA loss (middle) and Color Fill (bottom).

tency on the Classic Test Set, as its bounding box performs reasonably well when object shapes remain relatively unchanged. ReVideo degrades on multiple objects.

For object removal, we collect 15 videos with complex scenes, including object effects and occlusions, as existing test sets lack coverage of these cases. For SAM, we click on the object and side effects to ensure complete coverage. As shown in Tab. 2, GenProp achieves the highest consistency, while ReVideo may produce bounding box artifacts, and ProPainter struggles with object effects.

As quality metrics often do not correctly capture the realism of the generated results, we use Amazon MTurk [45] to conduct a user study with a total of 121 participants. Each participant views videos generated by GenProp and a random baseline, along with the original video and the text prompt. They are asked two questions: 1) Which video aligns better with the instructions? 2) Which video is visually better? Participants then select one video for each question. In Tables 1 and 2, we show the percentage of time users prefer Ours over the competing baselines (alignment/quality). GenProp outperforms all baselines by a large margin, especially on the Challenging Test Set.

4.3. Ablation Study

Mask Prediction Decoder In Tab. 3, we evaluate the effect of MPD on the Challenging Test Set, showing that it can improve both Text Alignment and Consistency. As shown in

Fig. 7 rows 1 and 2, without MPD, the output mask is often highly degraded, leading to worse removal quality. Without explicit supervision with MPD, the model may be confused which part to propagate and which part to preserve in the original video, causing partially removed objects to reappear in the following frames. MPD helps the disentanglement and both the removal results and predicted masks become more accurate with MPD, allowing for full object removal even with heavy occlusion.

Region-Aware Loss In Tab. 3, we further test the effectiveness of the proposed RA Loss on the Challenging Test Set. A core challenge in GenProp is that SCE can mistakenly select all regions from the original video including the edited areas, weakening the I2V generation ability due to the reconstruction loss. As shown in Fig. 7 rows 3-5, without RA Loss, the original object tends to gradually reappear, hindering the propagation of the first-frame edit (the green motor). With RA Loss, the edited areas are able to be propagated in a stable and consistent way.

Color Fill Augmentation Color Fill augmentation is another crucial factor for addressing the propagation failure. While copy-and-paste and mask-and-fill augmentations allow the model to implicitly learn object modifications, replacements, and deletions, color filling explicitly trains it for tracking, guiding the model to maintain modifications made in the first frame throughout the sequence, with the prompt "track colored regions". As shown in Fig. 7 rows 6-8, changing the girl into a small cat is challenging due to the significant shape difference. However, with color fill augmentation, GenProp successfully propagates this large modification throughout the sequence.

5. Conclusion

In this paper, we design a novel *generative video propagation* framework, GenProp, that harnesses the inherent video generation power of I2V models to achieve various downstream applications including removal, insertion and tracking. We demonstrate its potential by showing that it is able to expand the range of achievable edits (e.g., remove or track objects together with their associated effects) and generate highly realistic videos, without relying on traditional intermediate representations like optical flow or depth maps. By integrating a selective content encoder and leveraging an I2V generation model, GenProp consistently preserves unchanged content while dynamically propagating the changes. Synthetic data and the region-aware loss further enhance its ability to disentangle and refine edits across frames. Experimental results demonstrate its effectiveness, establishing it as a robust, flexible solution that surpasses prior methods in scope and precision. In the future, we plan to extend the model to take in more than one key frame edits and uncover additional video tasks that can be supported.

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