ProPainter

Improving **Propa**gation and **T**ransform**er** for Video Inpainting

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Video Inpainting

Video inpainting (VI): fill gaps or missing regions in a video with visually consistent content while ensuring spatial and temporal coherence.

video of DAVIS dataset and ProPainter result

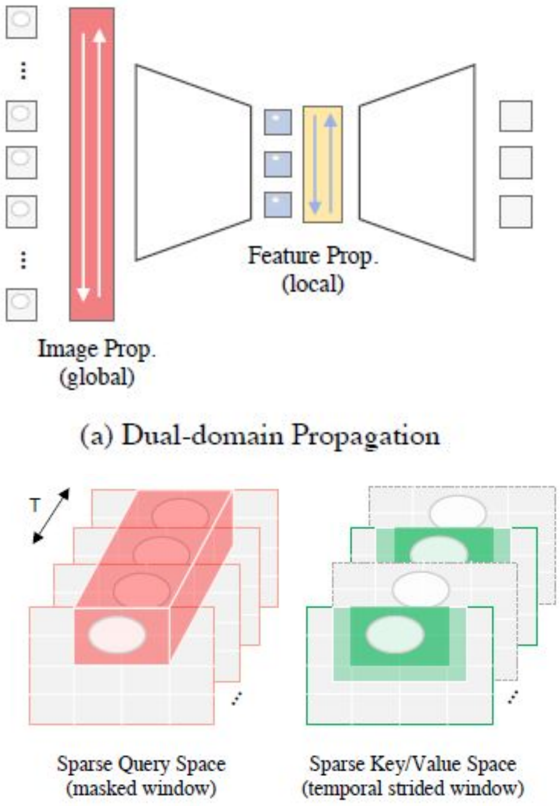
Main challenges

Challenge: Establish accurate correspondence across distant frames for information aggregation

1. **Memory** Constraint
2. **Computational** Constraint

Solutions:

1. Dual-domain Propagation
    - reduce computations
2. Mask-guided sparse video transformer
    - reduce memory



(a) Dual-domain Propagation

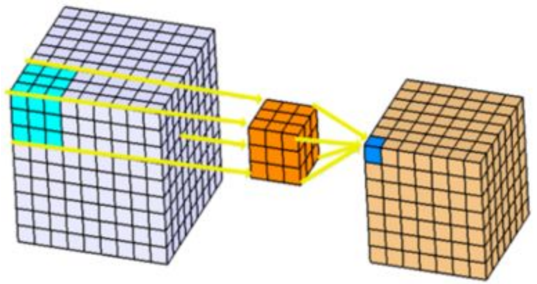
(b) Mask-guided Sparse Video Transformer

Less practical related works

3D CNNs:

Aggregate spatio-temporal information:

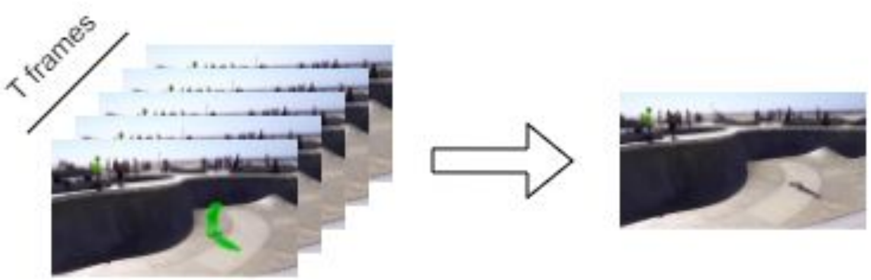
- Suffer from limited receptive fields in both temporal and spatial dimensions
- Less effective for exploring distant content



INTERNAL LEARNING:

Adopt internal learning to encode and memorize the appearance and motion of the video through deep networks:

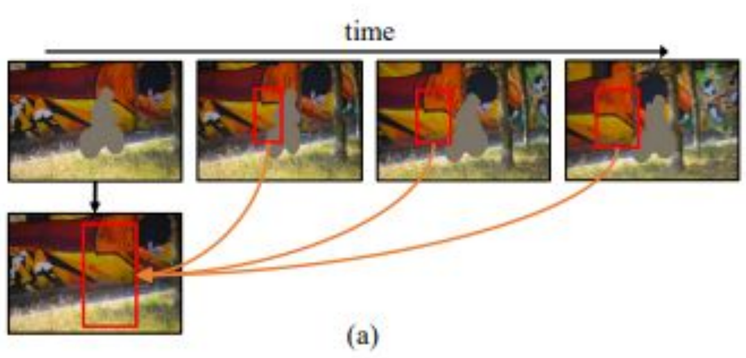
- Require individual training for each video.



Related works

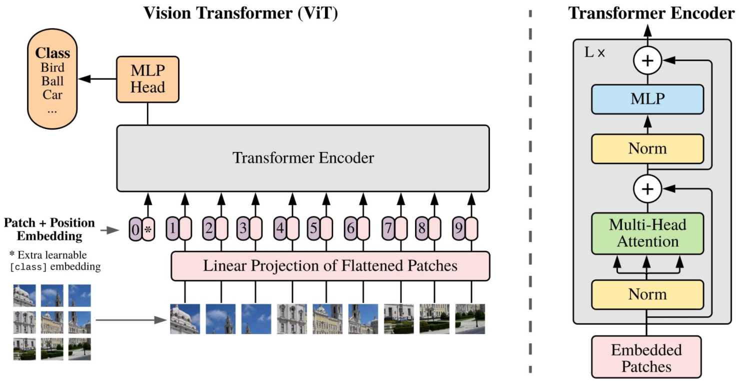
FLOW-GUIDED propagation:

Optical flow and **homography** to align neighboring reference frames to enhance temporal coherence and aggregation.

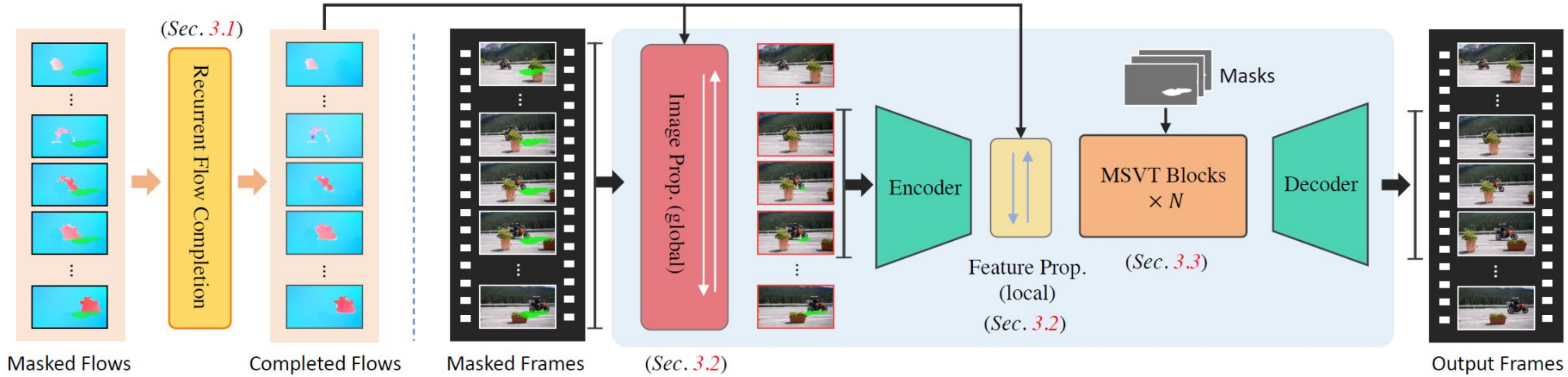


VIDEO TRANSFORMERS:

adopt spatio-temporal attention to explore recurrent textures in a video.



ProPainter: Architecture



Modules:

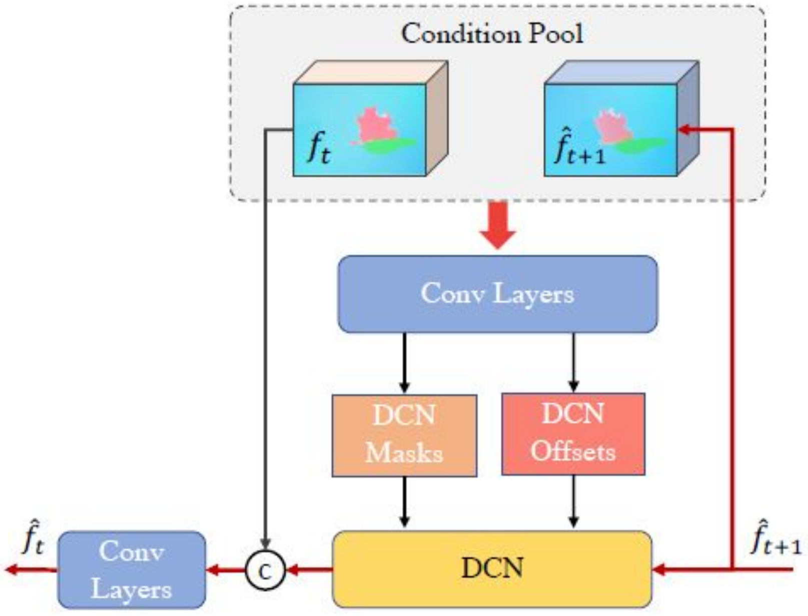
1. **Recurrent Flow Completion (RFC)** : flow field completion
2. **Dual-Domain Propagation (DDP)** : global image propagation and local feature propagation
3. **Mask-guided Sparse Video Transformer (MSVT)** : refine the propagation features and reconstruct the final video sequence

Recurrent Flow Completion (RFC)

use completed optical flow to propagate pixels and maintain temporal coherence.

- Recurrent network to compute forward and backward optical flows
- downsampled feature encoding
- **Deformable Convolution Network** (DCN) to bidirectionally propagate the flow information of adjacent frames
- Decoder to reconstruct the completed flows

$$\hat{f}_t = \mathcal{R}(\mathcal{D}(\hat{f}_{t+1}; o_{t\rightarrow t+1}, m_{t\rightarrow t+1}), f_t),$$



RFC: Flow-guided deformable alignment

1. spatial warping between optical flow of the previous frame and previous features

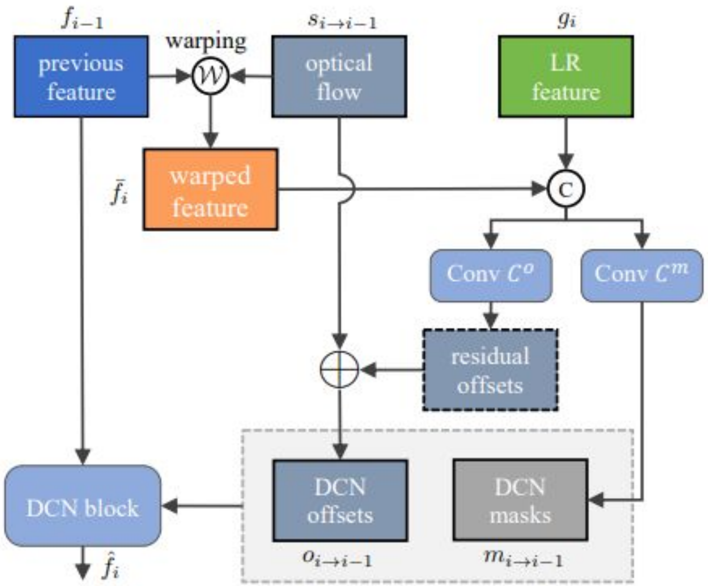
$$\bar{f}_{i-1} = \mathcal{W}(f_{i-1}, s_{i\rightarrow i-1})$$

2. compute the DCN offsets and modulation masks

$$o_{i\rightarrow i-1} = s_{i\rightarrow i-1} + C^{o}\left(c(g_i, \bar{f}_{i-1})\right)$$
$$m_{i\rightarrow i-1} = \sigma\left(C^{m}\left(c(g_i, \bar{f}_{i-1})\right)\right).$$

3. DCN applied to the unwarped feature

$$\hat{f}_i = \mathcal{D}\left(f_{i-1}; o_{i\rightarrow i-1}, m_{i\rightarrow i-1}\right)$$

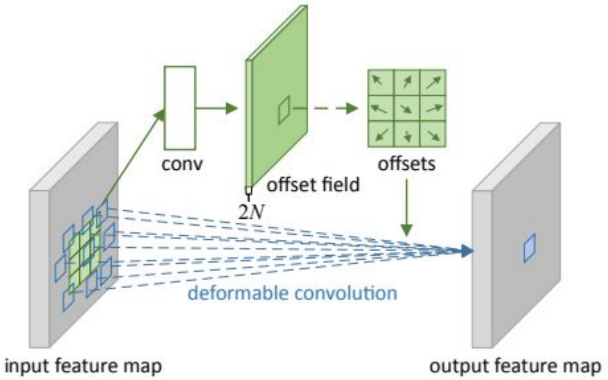


RFC: Deformable Convolution Network (DCN)

- **Deformable convolution**

augment the grid with optical flow offsets

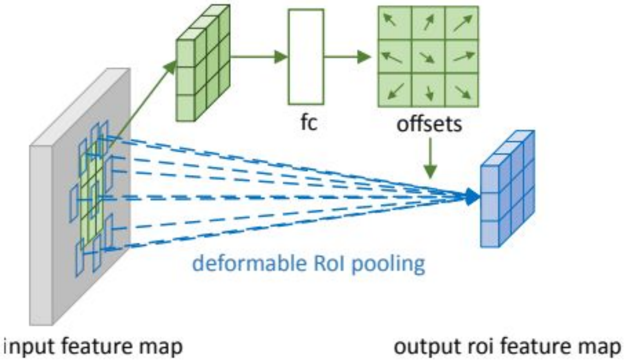
$$\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n + \Delta \mathbf{p}_n).$$



- **Deformable RoI Pooling**

offsets are added to the spatial binning

$$\mathbf{y}(i,j) = \sum_{\mathbf{p} \in bin(i,j)} \mathbf{x}(\mathbf{p}_0 + \mathbf{p} + \Delta \mathbf{p}_{ij}) / n_{ij}.$$



RFC: Separate modules require separate losses

- **Reconstruction loss**

  applied to both valid and invalid regions

$$\mathcal{L}_{rec}^{flow} = \frac{\left\| M_t \odot (\hat{F}_t - F_t) \right\|_1}{\|M_t\|_1} + \frac{\left\| (1 - M_t) \odot (\hat{F}_t - F_t) \right\|_1}{\|1 - M_t\|_1},$$

- **Smooth loss**

  divergence operator to encourage the coherence of completer flow fields

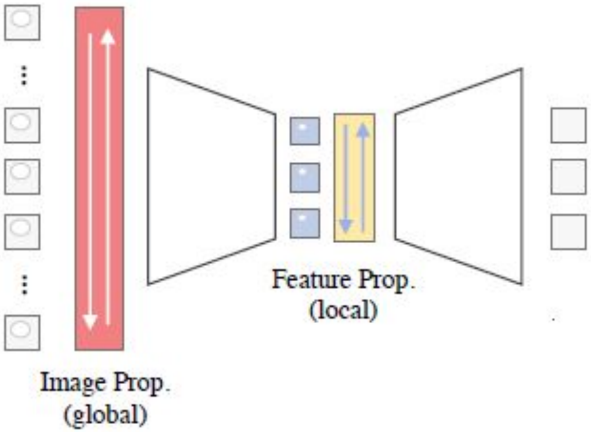
$$\mathcal{L}_{smooth}^{flow} = \left\| \Delta \hat{F}_t \right\|_1,$$

Dual-Domain Propagation (DDP)

- **GLOBAL** propagation in the **image domains**
- **LOCAL** propagation in the **feature domains**

Distinct alignment operations and strategies for each domain is employed.

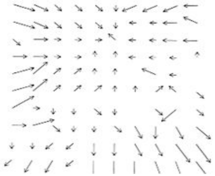
Both domains involve bidirectional propagation in the forward and backward directions.



(a) Dual-domain Propagation

DDP: image propagation with flow-based warping

INPUT: video sequence w/mask, completed flows F



The process start with the identification of the **reliable propagation area** Ar:

$$A_r(p) = \begin{cases} 1 & \text{if } p \in C_1 \cap C_2 \cap C_3, \\ 0 & \text{otherwise.} \end{cases}$$

where ***C1,C2,C3*** are constraints and ***p*** denotes pixel position of the current frame.

DDP: image propagation

$$A_r(p) = \begin{cases} 1 & \text{if } p \in C_1 \cap C_2 \cap C_3, \\ 0 & \text{otherwise.} \end{cases}$$

- **C1**: only pixels with a s**mall consistency error** will be propagated.

$$C_1 : \mathcal{E}_{t\to t+1}(p) < \epsilon \qquad \mathcal{E}_{t\to t+1}(p) = \left\| \hat{F}_{t\to t+1}(p) + \hat{F}_{t+1\to t}(p + \hat{F}_{t\to t+1}(p)) \right\|_2^2,$$

- **C2**: only consider **the masked areas** of the current frame Xt that needs to be filled

$$C_2 : M_t(p) = 1,$$

- **C3**: only propagate the **unmasked areas** from neighboring frame Xt+1

$$C_3 \ : \ M_{t+1}(p + \hat{F}_{t\to t+1}(p)) \ = \ 0.$$

The process of image propagation is expressed as:

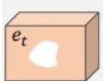
$$\hat{X}_t = \mathcal{W}(X_{t+1}, \hat{F}_{t\to t+1}) * A_r + X_t * (1 - A_r),$$

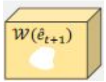
DDP: feature propagation

An **image encoder** is used for extracting the features.

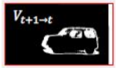
A **flow-guided deformable alignment module** for feature propagation is adopt, similar to the one in the RFC component.

It differs for the conditions for learning DCN offsets:

- current feature 

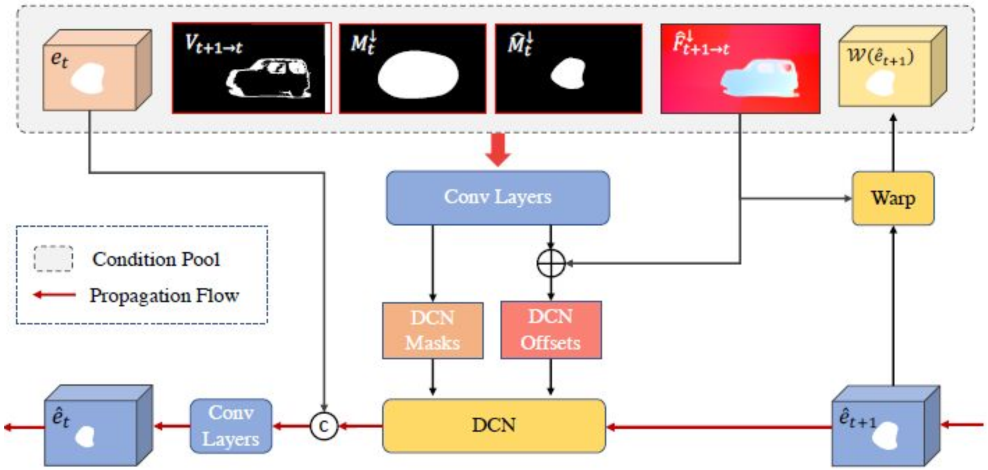
- warped propagation feature 

- completed flows 

- the flow valid map 

- original mask 

- updated mask 

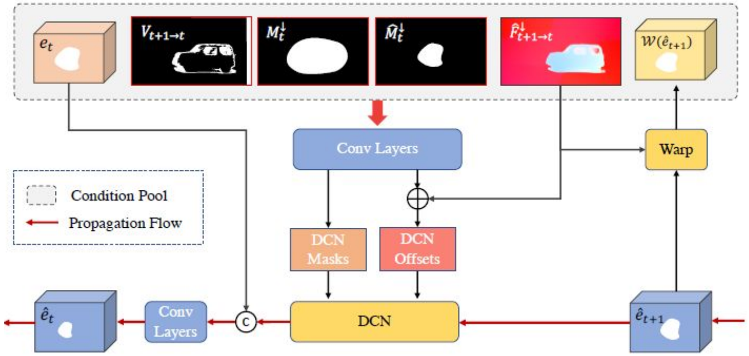


DDP: feature propagation

With these conditions, a stack of **convolutions** is employed to predict the **DCN offset residue** and **modulation masks**.

A **DCN** is then applied to **align** the propagation feature from the previous frame.
DCN alignment propagation is expressed, similar to the previous, as:

$$\hat{e}_t = \mathcal{R}(\mathcal{D}(\hat{e}_{t+1}; \hat{F}^{\downarrow}_{t\rightarrow t+1} + \widetilde{o}_{t\rightarrow t+1}, m_{t\rightarrow t+1}), f_t)$$



Finally, a **CNN block** is employed to fuse the current and aligned features, achieving **the propagation feature** of the current frame.

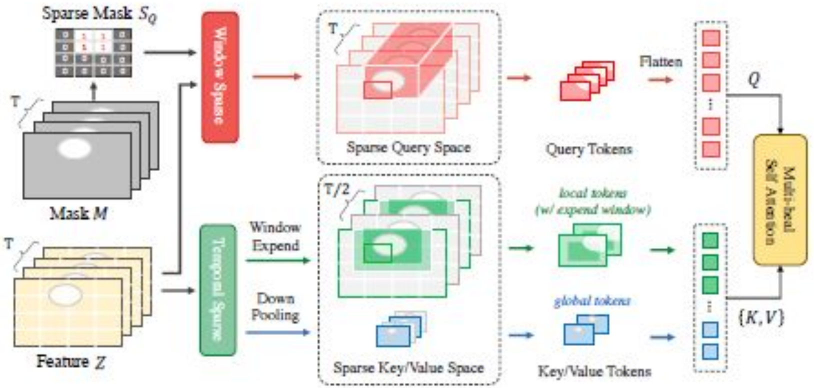
Mask-guided Sparse Video Transformer (MSVT)

Novel sparse video Transformer that builds on the window-based approach.

From video sequence feature use **soft split operator** for having many overlapping patches.

The **query Q**, **key K**, and **value V** are obtained through **linear layers**, from the patches.

Sparse strategies designed to reduce memory and computation



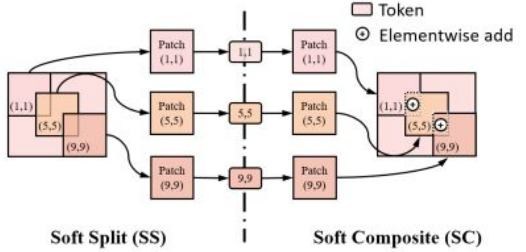


Figure 3. The illustration of Soft Split (SS) and Soft Composite (SC) module.

MSVT: SPARSE QUERY SPACE

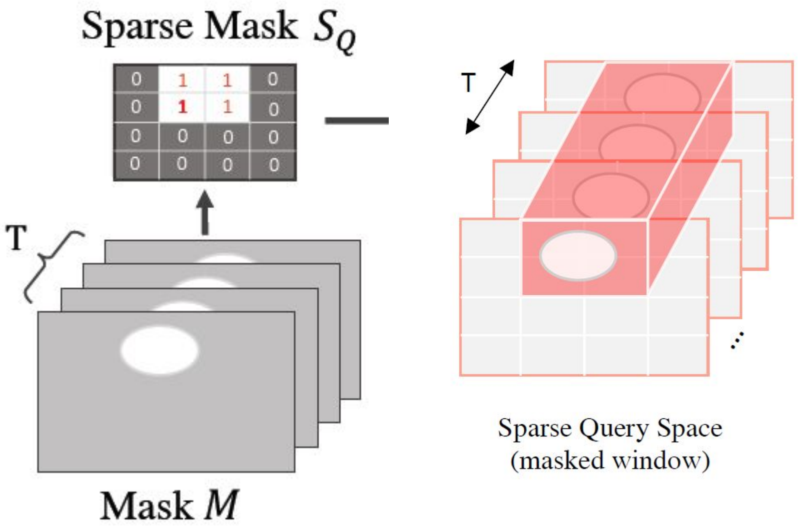
The **mask** is usually **small** in reference to the full video frame, and **spatiotemporal attention** may not be necessary for all query windows

Apply attention only to query windows that intersects with mask regions.

- the masks are downsampled and partitioned
- sum it up in the temporal dimension

To obtain sparse mask S_Q

$$S_Q = Clip\left(\sum_{t=1}^{T_l} M_t^{\downarrow}, 1\right),$$

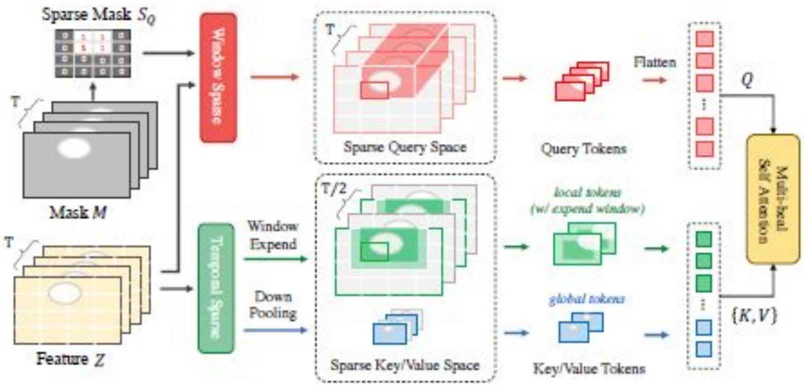


MSVT: SPARSE KEY/VALUE SPACE

Due to the highly redundant and repetitive textures in adjacent frames, it is unnecessary to include all frames as key/value tokens in each Transformer block.

Only include strided temporal frames alternately, with a temporal stride of 2 in the design.

By doing so, the key and value space is reduced by half, effectively reducing the computation and memory cost of the Transformer module.

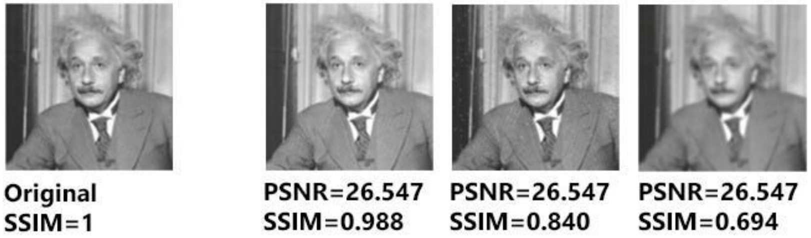


Metrics

Metrics:

- **Peak Signal-to-Noise Ratio (PSNR)**
  - the ratio between the maximum possible value of a signal and the value of distorting noise that affects the quality of its representation

- **Structural Similarity Index Measure (SSIM)**
  - It considers luminance, contrast, and structure, comparing the local patterns of pixel intensities in the original and distorted images.



Results

Paper results

	ProPainter
PSNR ↑	34.47
SSIM ↑	0.9776

50 video clips,
from DAVIS dataset

Our results

	ProPainter
PSNR ↑	23.536
SSIM ↑	0.912

90 video clips 854 × 480,
from DAVIS dataset with half precision inference.

psnr = 13.520
ssim = 0.8523

psnr = 32.312
ssim =0.9905

↑ higher value is better

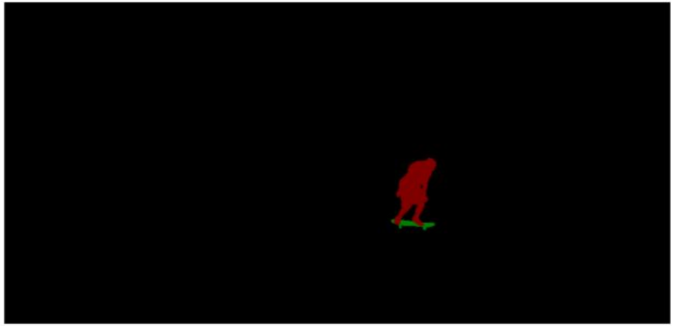
PROPOSED IMPROVEMENTS

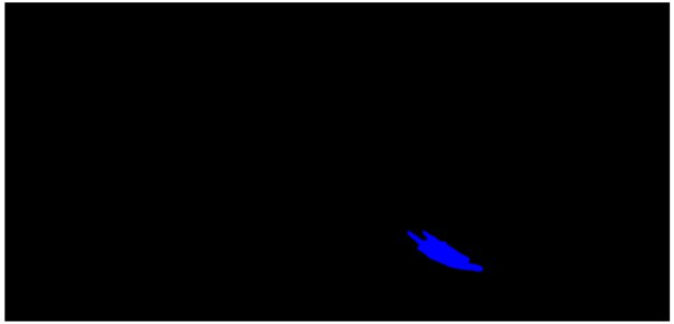
- qualitative experiments:
  - shadow detection and removal
  - single/multi-prompt detection and removal
- new sparse strategy
- improving video inpainting with diffusion model (?)

Shadow detection and removal

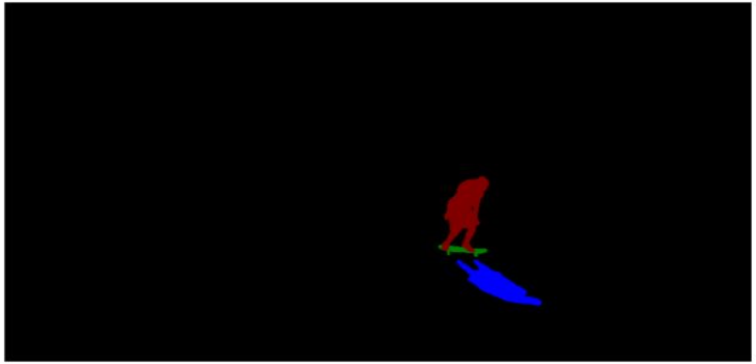
Using Segment Anything Model (SAM) to segment shadow masks in each frame

Shadow detection and removal





- Add up the segmented shadow mask with the original one



- Use propainter for the impainting

Shadow detection and removal: results

Multi-stage approach for object removal by textual prompts

4 Models in a cascade in order to remove objects in video sequences:

- **Yolov8** - Object Detection in the scene
- **Clip** - Select object based on the input textual prompt
- **SAM** - Segmentation of the objects
- **ProPainter** - Object removal given the segmented masks

spatial information between frames has been added during the object detection phase in order to be consistent with the video sequences.

Results: Paragliding

Textual prompt = “The white and red glider”

Results: Stroller

Textual Prompt: “The person with a white shirt”

Multi-stage approach for object removal: Drawbacks

- **Multi-stage curse**: Since the models are used in a cascade approach, if one of them fails into doing the inference , the whole network will fail
- **Limited number of classes**: the models are pre-trained on a fixed number of classes (expecially yolov8 has in total 80 classes) , so i can't remove objects out of those classes.

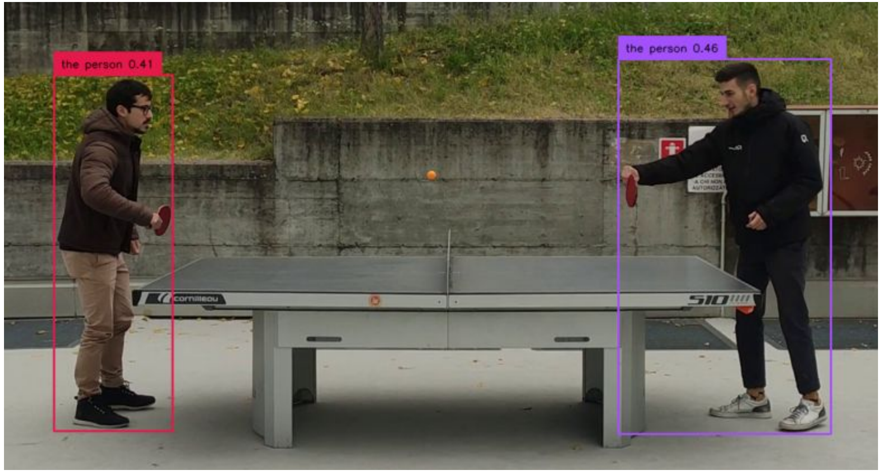
Textual Prompts Object Removal with GroundingDINO

- **Single Prompt**

Text = 'The small orange ball'

- **Multi Prompt**

Text = 'The person on the right and the person on the left'



GroundingDINO : Results

Original Video

Single Prompt Inpainting

GroundingDINO : Results

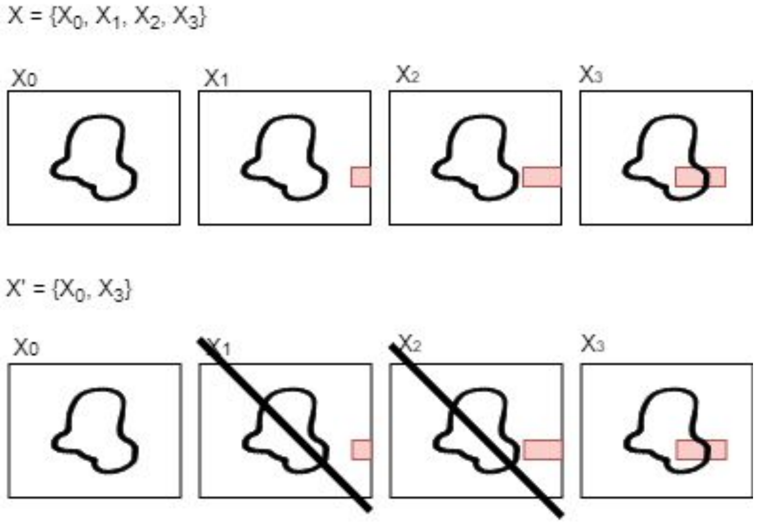
Original Video

Multi Prompt Inpainting

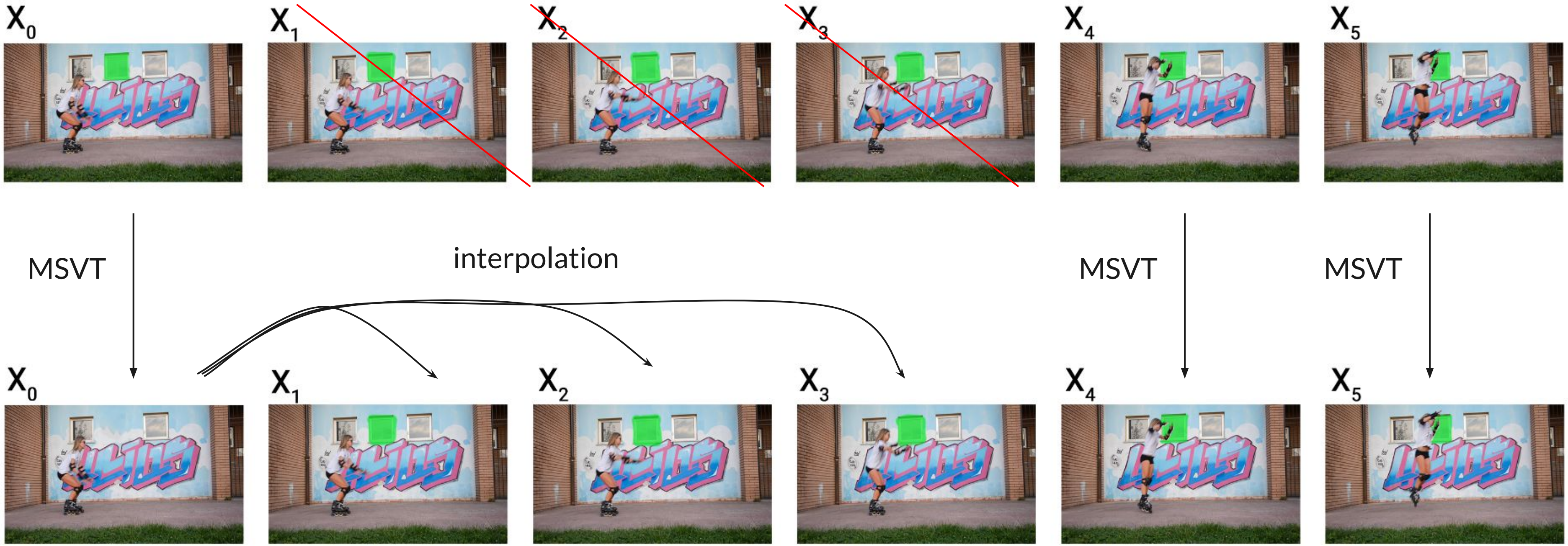
NEW SPARSE STRATEGY: adaptive sparse video transformer for fast computing during static frames

GOAL: leveraging the temporal coherence of low-motion regions.

As input for the MSVT we reduce the sequences X by $$X' = X - \sum_{t=1}^{T} Match_t(|O_{t-1} - O_t| \leq \gamma, X_t) \quad \gamma \simeq 0$$

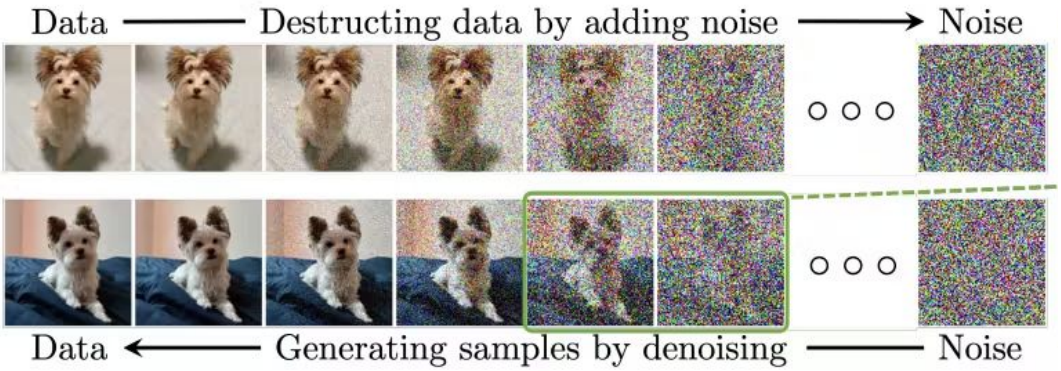


$X' = X_0, X_4, X_5$



Improving video inpainting with diffusion model (?)

Diffusion models are **generative models**, that generate new data from a noisy space using denoising techniques and conditioning to achieve desired results.

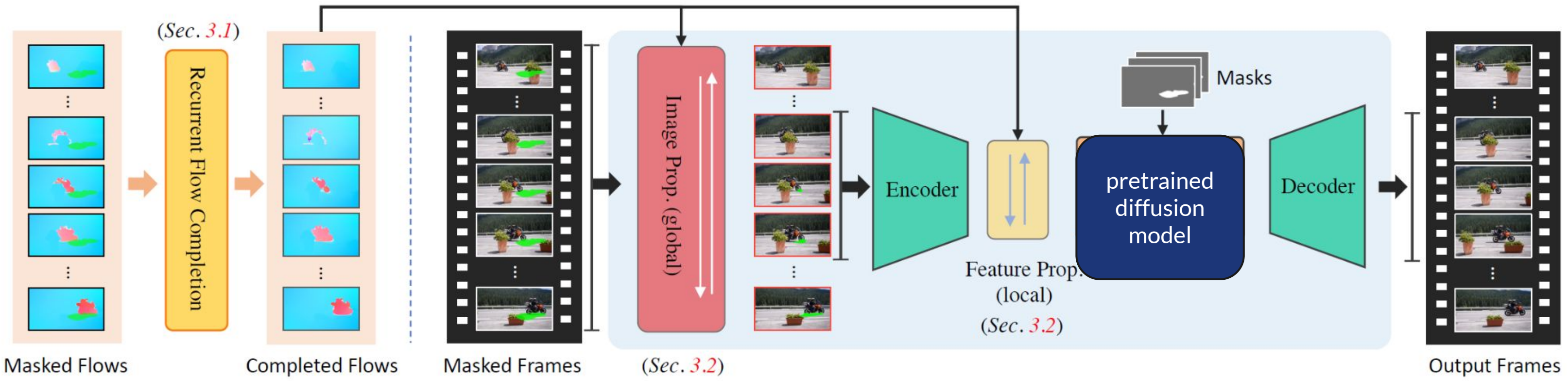


Video inpainting with diffusion models is often treated as an **internal learning** task, demonstrating high accuracy but at the expense of a slower computational speed.

Improving video inpainting with diffusion model

OUR IDEA:

- substitute the MSVT block with a **pretrained diffusion model** fine tuned for video
- use features and optical flow as **conditioning**



Pros

Some **advantages** of using diffusion models are:

- better **quality**
- better **results** in non conventional cases

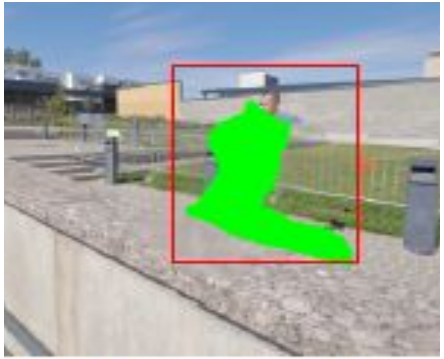


image with mask

Propainter

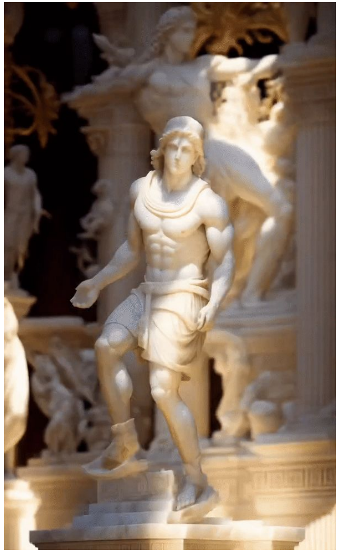
Dall-e2, prompt:”infill according to the background”

Cons

SLOW INFERENCE

possible solutions:

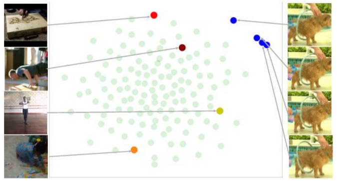
- use lower quality models,
- sparse strategy with interpolation



TEMPORAL CONSISTENCY (flickering problem)

possible solutions:

- **sampling of noise for better correlation**
  Preserve Your Own Correlation: A Noise Prior for Video Diffusion Models (ICCV'23)
- **temporal layers**
  Stable Video Diffusion: Scaling Latent Video Diffusion Models to Large Datasets



Thank you for the attention

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