Clearer Frames, Anytime: Resolving Velocity Ambiguity in Video Frame Interpolation

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Outline

- Introduction: **Video frame interpolation**
- Problem: **Velocity ambiguity in time indexing**
- Methodology: **Strategies for disambiguation**
- Experiment: **Effectiveness of plug-and-play strategies**
- New feature: **Manipulated interpolation of anything**
- Conclusion and future work

Introduction: **Video frame interpolation**

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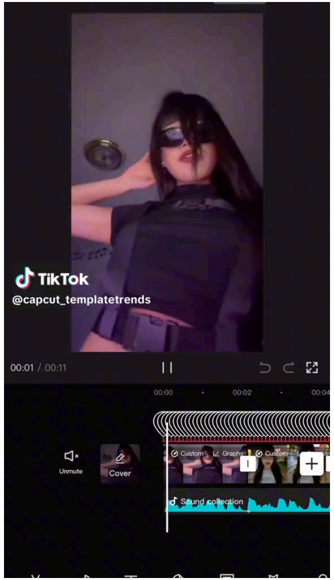
- Video frame interpolation (VFI) has wide applications

Slow motion of highlights

Sync video to the beat



Assisting video generation

Video compression

H.264
MPEG-4/AVC

Introduction: **Paradigms**

- Traditional flow-based approaches: **linear motion; holes**
- Learning-based approaches include **fixed-time** & **arbitrary-time** interpolation
- Arbitrary-time: **faster for any timestep; no accumulation errors**

$$I_t = \mathcal{F}\left(I_0, I_1, t\right).$$

I_0

I_1

arbitrary time $t \in [0, 1]$

Problem: **Velocity ambiguity in time indexing**

- The velocities of individual objects within starting and ending frames remain undefined, introducing a velocity ambiguity, a myriad of plausible time-to-location mappings during training

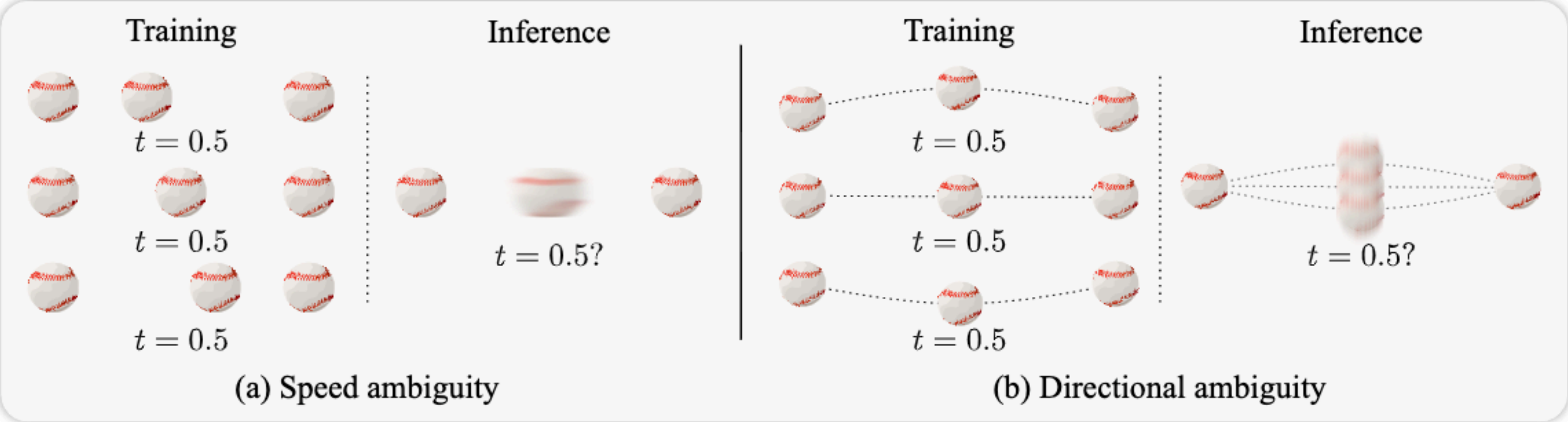
$$\{I_t^1, I_t^2, \ldots, I_t^n\} = \mathcal{F}(I_0, I_1, t),$$

- As a result, models trained with ***time indexing*** tend to produce blurred and imprecise interpolations, as they average out the potential outcomes.

$$\hat{I}_t = \mathbb{E}_{I_t \sim \mathcal{F}(I_0, I_1, t)}[I_t].$$

Problem: **Velocity ambiguity in time indexing**

- Velocity ambiguity encompasses **speed ambiguity** & **directional ambiguity**



Methodology: **Strategies for disambiguation**

- ***Could an alternative indexing method minimize such conflicts?***

$$\boxed{I_t = \mathcal{F}\left(I_0, I_1, \text{motion hint}\right) \Rightarrow I_t = \mathcal{F}\left(I_0, I_1, D_t\right).}$$

- Optical flow? → Unknown at inference time

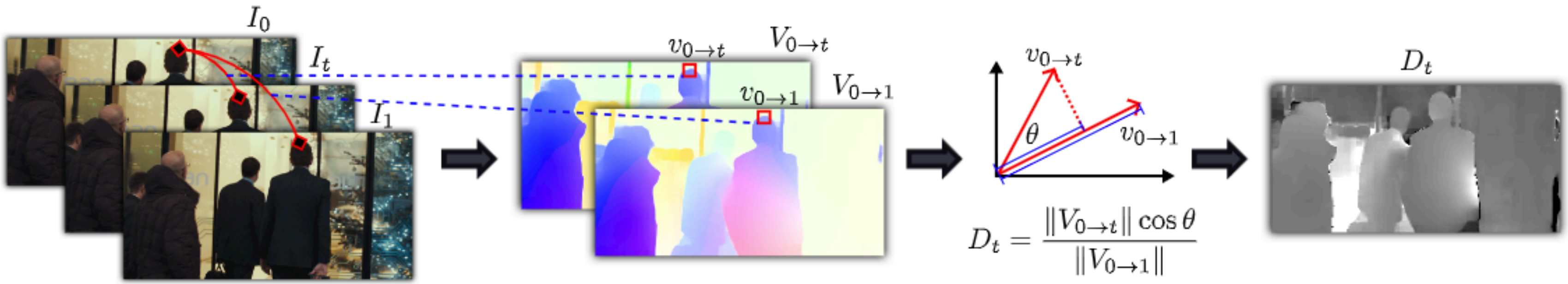
- Instead, we propose a more flexible ***distance indexing*** approach. We employ a ***distance ratio*** map D_t, where each pixel denotes ***how far the object has traveled between start and end frames***, within a normalized range of [0,1]

Methodology: **Distance indexing**

- We guide the network to interpolate more precisely without relying on the ambiguous time-to-location mapping to decipher it independently

$$I_t = \mathcal{F}(I_0, I_1, \mathcal{D}(t)). \quad \rightarrow \quad I_t = \mathcal{F}(I_0, I_1, D_t).$$

- ***In practice, we notice it is sufficient to provide a uniform map $D_t = t$, similar to time indexing (move each object at constant speeds along trajectories)***



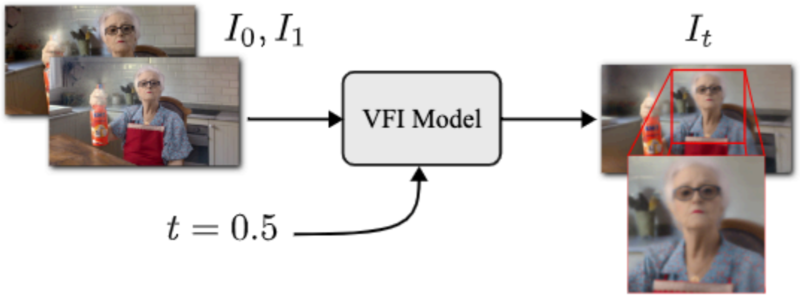
Methodology: **Iterative reference-based estimation**

- Although ***distance indexing (a)*** addresses the scalar ***speed ambiguity***, the ***directional ambiguity*** of motion remains a challenge.
- We introduce an ***iterative reference-based estimation strategy (b)***,which incrementally estimates distances, beginning with nearby points and advancing to farther ones, to mitigate the remained ambiguity

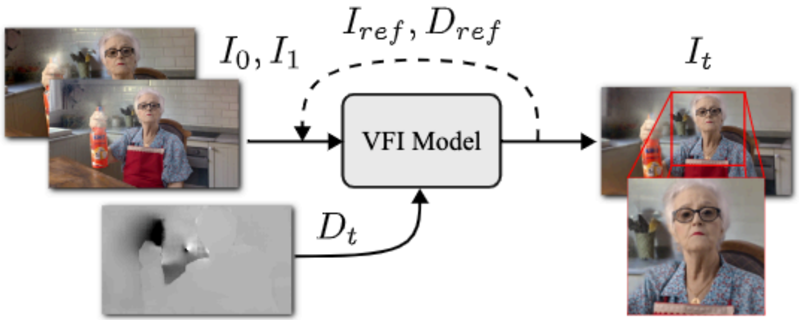
(a) Distance indexing (b) Reference-based estimation

Methodology: **Plug-and-play**

- Our approach addresses challenges that are not bound to specific network architectures. Indeed, it can be applied as a plug-and-play strategy that requires only modifying the input channels for each model



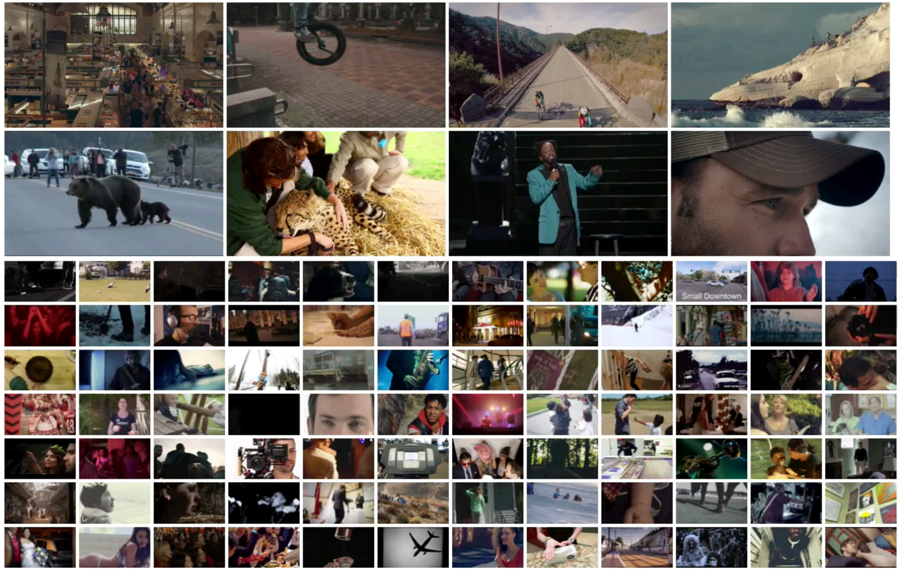
(a) Training paradigm of time indexing



(b) Training paradigm of distance indexing

Experiments: **Vimeo90K septuplet dataset**

- Consists of 91,701 seven frame sequences with fixed resolution 448 x 256, extracted from 39,000 selected video clips



Experiment: **State-of-the-art models**

- [ECCV 2022] Real-Time Intermediate Flow Estimation for Video Frame Interpolation
- [CVPR 2022] IFRNet: Intermediate Feature Refine Network for Efficient Frame Interpolation
- [CVPR 2023] Extracting Motion and Appearance via Inter-Frame Attention for Efficient Video Frame Interpolation (EMA-VFI)
- [CVPR 2023] AMT: All-Pairs Multi-Field Transforms for Efficient Frame Interpolation
- **[T] time indexing; [D] distance indexing; [R] reference-based estimation**

Experiment: **Qualitative**

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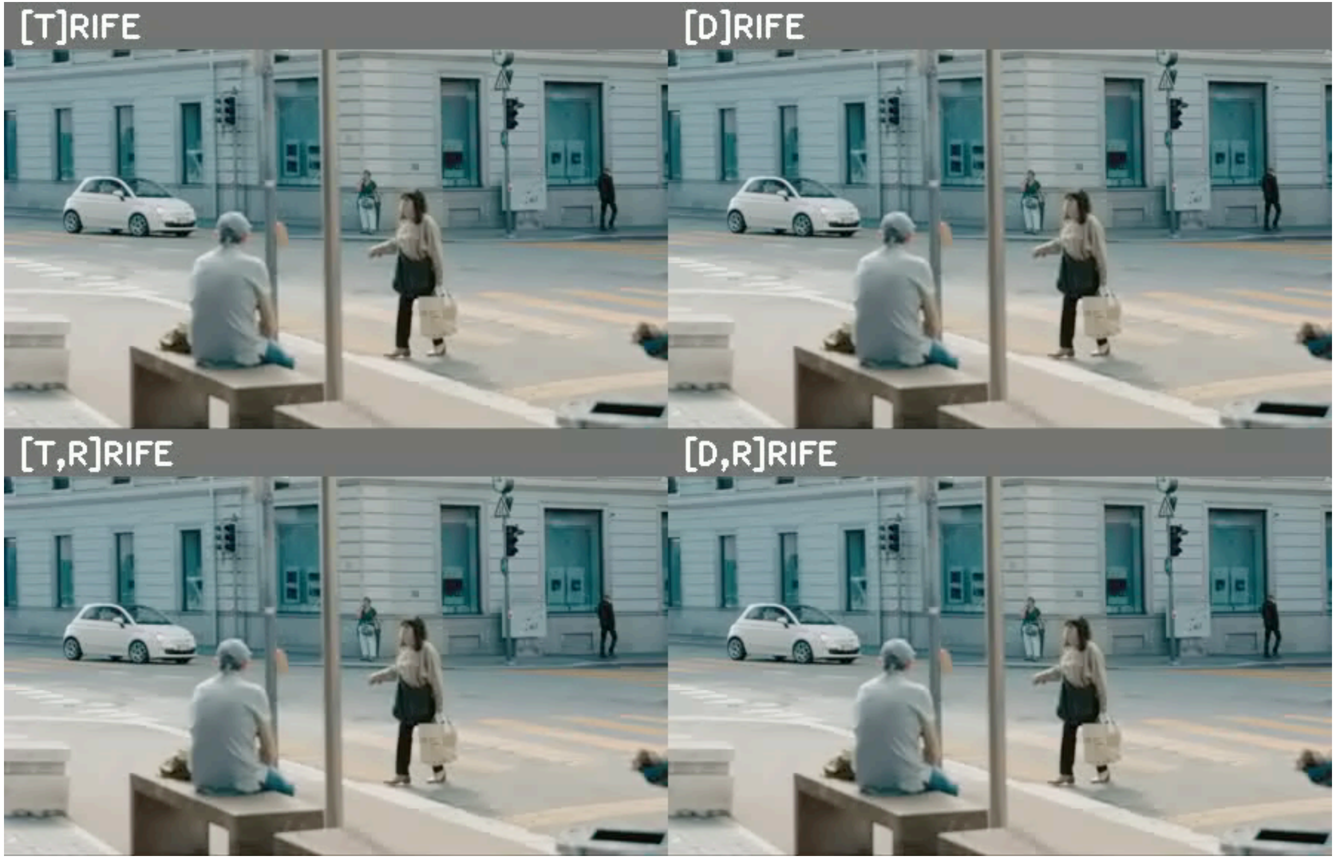

Experiment: **Quantitative**

Table 1: Comparison on Vimeo90K Septuplet dataset. $[T]$ denotes the method trained with traditional arbitrary time indexing paradigm. $[D]$ and $[R]$ denote the distance indexing paradigm and iterative reference-based estimation strategy, respectively. $[R]$ uses 2 iterations by default. $[\cdot]_u$ denotes inference with uniform map as time indexes. The **bold font** denotes the best performance in cases where comparison is possible. While the gray font indicates that the scores for pixel-centric metrics, PSNR and SSIM, are not calculated using strictly aligned ground-truth and predicted frames.

	RIFE Huang et al. (2022)			IFRNet Kong et al. (2022)			AMT-S Li et al. (2023)			EMA-VFI Zhang et al. (2023)		
	$[T]$	$[D]$	$[D,R]$	$[T]$	$[D]$	$[D,R]$	$[T]$	$[D]$	$[D,R]$	$[T]$	$[D]$	$[D,R]$
PSNR ↑	28.22	**29.20**	28.84	28.26	**29.25**	28.55	28.52	**29.61**	28.91	29.41	**30.29**	25.10
SSIM ↑	0.912	**0.929**	0.926	0.915	**0.931**	0.925	0.920	**0.937**	0.931	0.928	**0.942**	0.858
LPIPS ↓	0.105	0.092	**0.081**	0.088	0.080	**0.072**	0.101	0.086	**0.077**	0.086	**0.078**	0.079
NIQE ↓	6.663	6.475	**6.286**	6.422	6.342	**6.241**	6.866	6.656	**6.464**	6.736	6.545	**6.241**
	$[T]$	$[D]_u$	$[D,R]_u$	$[T]$	$[D]_u$	$[D,R]_u$	$[T]$	$[D]_u$	$[D,R]_u$	$[T]$	$[D]_u$	$[D,R]_u$
PSNR ↑	28.22	27.55	27.41	28.26	27.40	27.13	28.52	27.33	27.17	29.41	28.24	24.73
SSIM ↑	0.912	0.902	0.901	0.915	0.902	0.899	0.920	0.902	0.902	0.928	0.912	0.851
LPIPS ↓	0.105	0.092	**0.086**	0.088	0.083	**0.078**	0.101	0.090	**0.081**	0.086	**0.079**	0.081
NIQE ↓	6.663	6.344	**6.220**	6.422	6.196	**6.167**	6.866	6.452	**6.326**	6.736	6.457	**6.227**

Experiment: **Quantitative**

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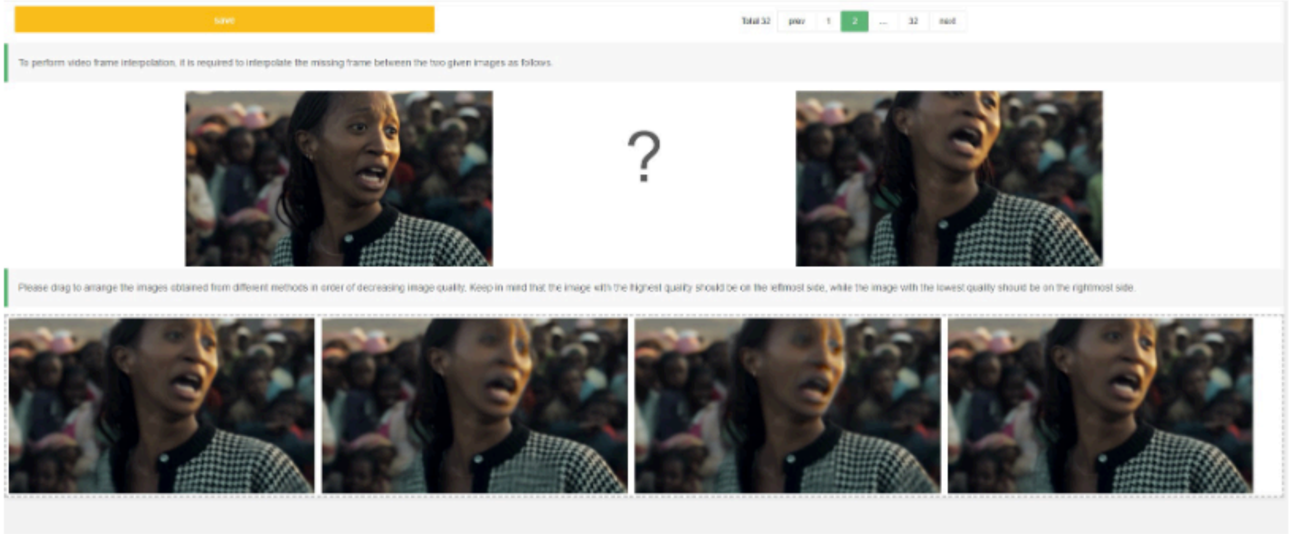
Table 2: Ablation study of the number of iterations on Vimeo90K Septuplet dataset. $[\cdot]^{\#}$ denotes the number of iterations used for inference.

	RIFE Huang et al. (2022)			IFRNet Kong et al. (2022)			AMT-S Li et al. (2023)			EMA-VFI Zhang et al. (2023)		
$[D, R]_u$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$
LPIPS ↓	0.093	0.086	**0.085**	0.085	**0.078**	0.078	0.086	**0.081**	0.081	0.084	0.081	**0.080**
NIQE ↓	6.331	6.220	**6.186**	6.205	6.167	**6.167**	6.402	**6.326**	6.327	6.303	6.227	**6.211**
$[T, R]$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$	$[\cdot]^1$	$[\cdot]^2$	$[\cdot]^3$
LPIPS ↓	0.103	0.087	**0.087**	0.091	0.084	**0.084**	**0.106**	0.135	0.157	0.088	**0.083**	0.085
NIQE ↓	6.551	6.300	**6.206**	6.424	6.347	**6.314**	**6.929**	7.246	7.502	6.404	6.280	**6.246**

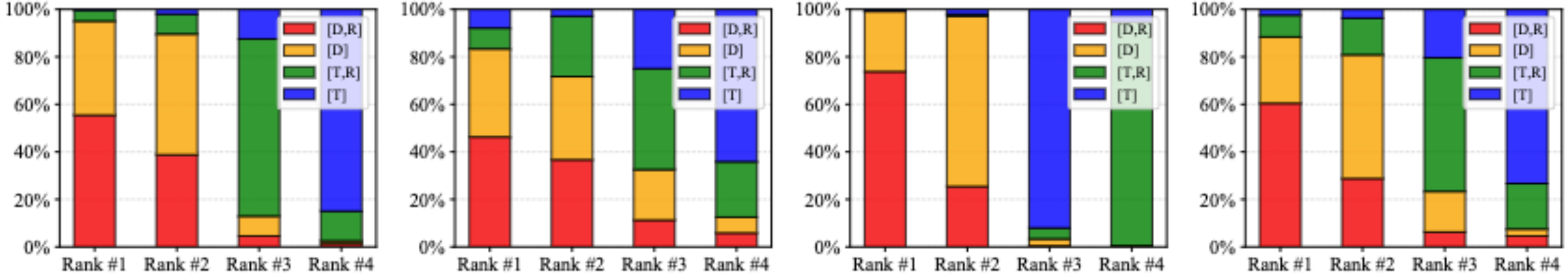
Experiment: **User study**

- Questionnaire statistics of VFI model's performance (Webapp)
- Ranking of [T], [D], [T,R], and [D,R]
- 30 anonymous participants



Experiment: **User study**

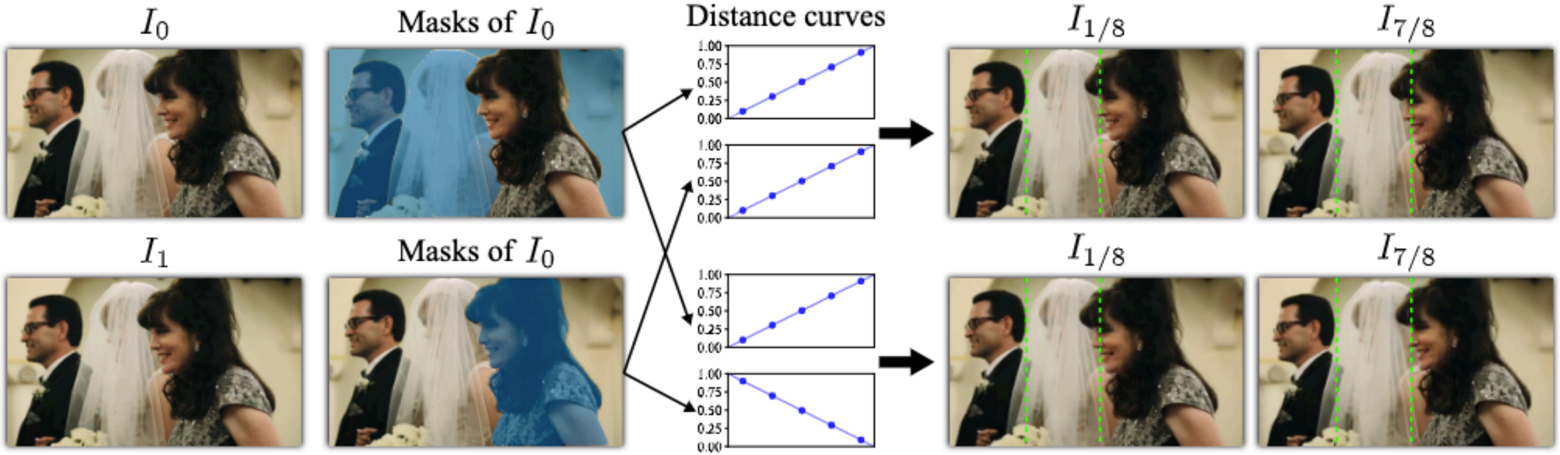
- The results align with our qualitative and quantitative findings. The [D,R] model variant emerged as the top-rated, underscoring the effectiveness of our strategies



(a) RIFE (b) IFRNet (c) AMT-S (d) EMA-VFI

New Feature: **Manipulated interpolation of anything**

- Instead of using a uniform map, it is also possible to use a spatially-varying 2D map as input to manipulate the motion of objects. Paired with SOTA segmentation models such as SAM, this empowers users to freely control the interpolation of any object, *e.g.*, making certain objects backtrack in time



New Feature: **Manipulated interpolation of anything**

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I_0

I_1

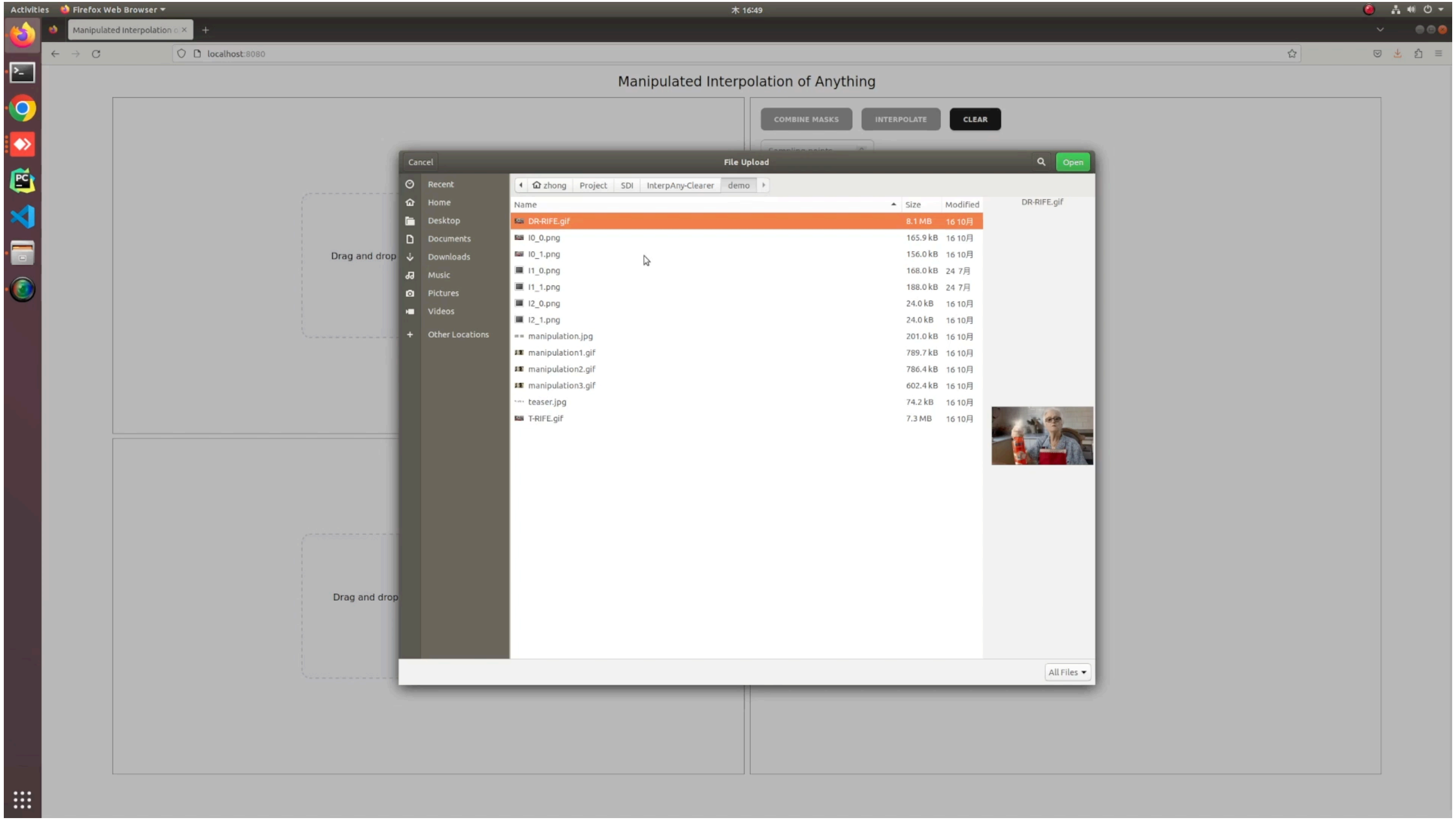
Uniform interpolation

Manipulated mask

Inverse distance within mask

Set 0 for the rest

New Feature: **Demo of webapp**



Conclusion and future work

- We propose distance indexing and iterative reference-based estimation to address the velocity ambiguity and enhance the capabilities of arbitrary time interpolation models

- We present an unprecedented manipulation method that allows for customized interpolation of any object

- Using multiple frames to estimate an accurate distance ratio map for a specific object is one of future works