Lumiere: A Space-Time Diffusion Model for Video Generation

Omer Bar-Tal, Hila Chefer, Omer Tov, Charles Herrmann, Roni Paiss, Shiran Zada, Ariel Ephrat, Junhwa Hur, Guanghui Liu, Amit Raj, Yuanzhen Li, Michael Rubinstein, Tomer Michaeli, Oliver Wang, Deqing Sun, Tali Dekel, Inbar Mosseri

SIGGRAPH 2024, 259 citations

Presented by:
Anantapadmanaabha Prasannakumar

Outline

- Motivation
- Method
- Evaluations
- Applications
- Societal Impact
- Limitations
- Conclusion

Motivation

- Restricted capability of existing models
  - Sensitive to error
  - Suffers from memory and computing constraints
  - Obtaining large-scale data is cumbersome
  - Training large-scale T2V is challenging

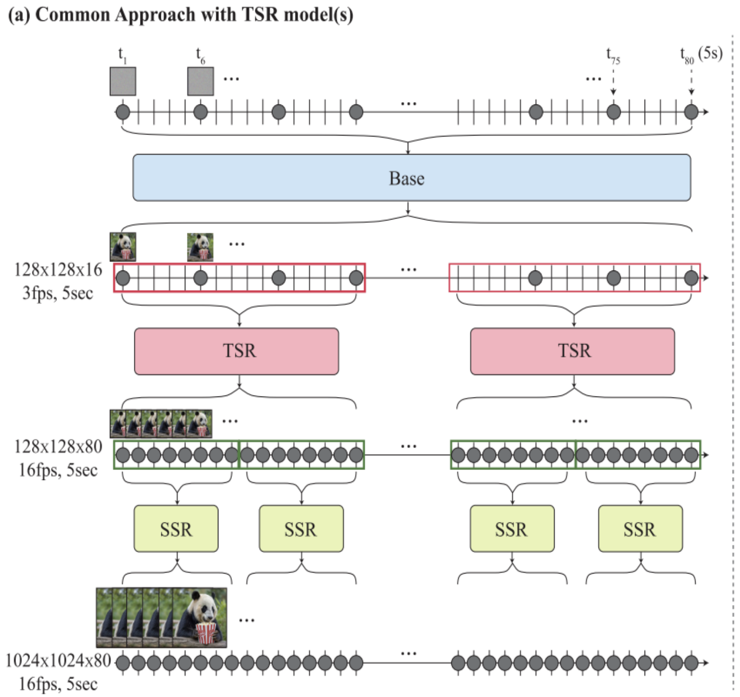
Motivation

- Employing temporal cascades is hindersome
  - Generates aggressively sub-sampled set of keyframes
  - TSR modules are constrained to fixed, small temporal context
  - Cascaded training suffers from domain gap

Method - Lumiere

- Utilizes Diffusion Probabilistic Models
  - Through denoising steps, trained to approximate data distribution
  - Starting from noise, a clean sample is drawn from the targeted distribution
- Incorporates additional guiding signals

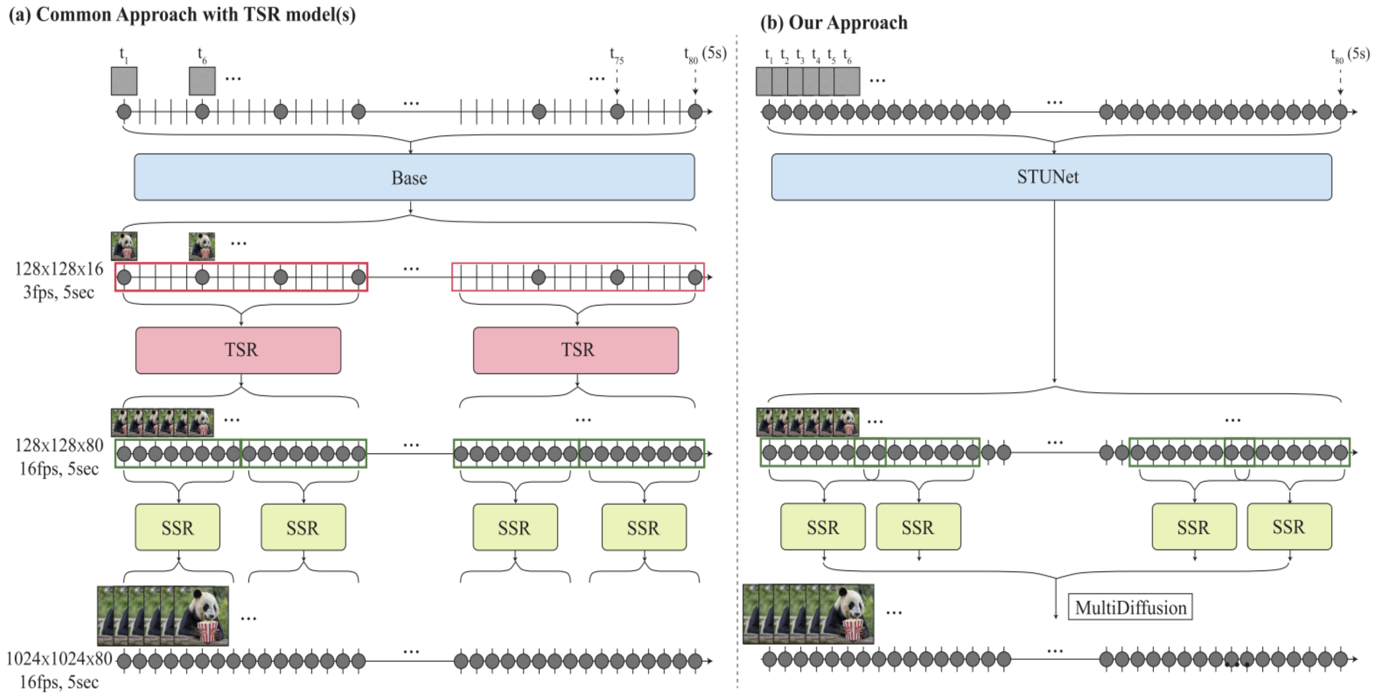
Method - Pipeline



Common T2V Framework:

- Base Model
- Temporal Super-resolution Model (TSR)
- Spatial Super-resolution Model (SSR)

Method - Pipeline

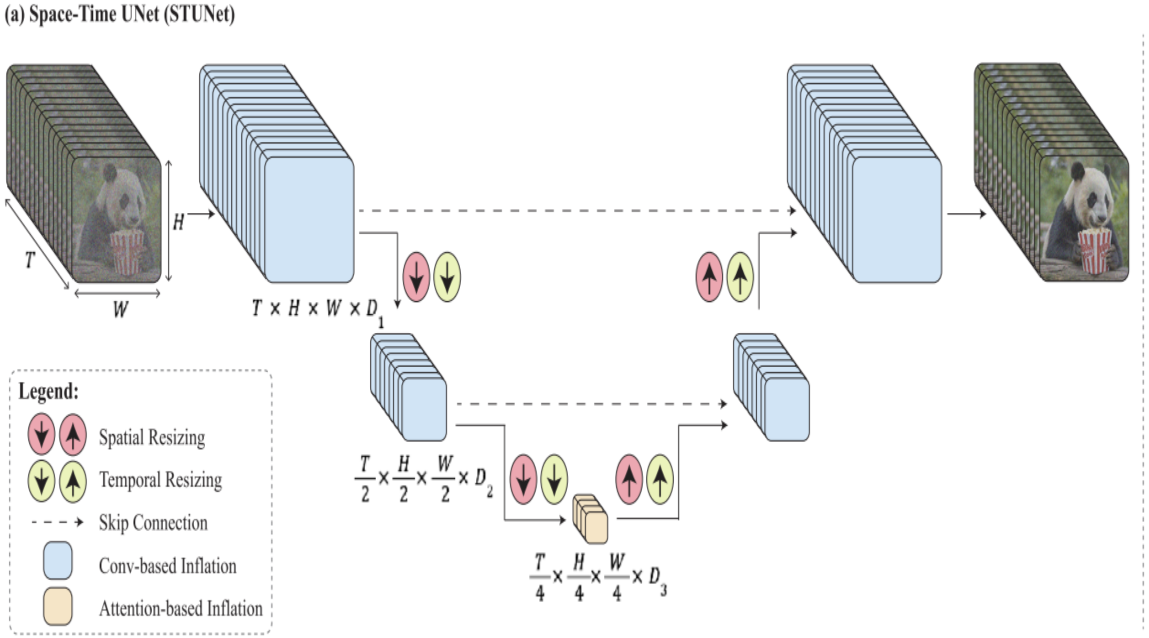


Lumiere Framework:

- Base Model
- Spatial Super-resolution Model (SSR)
- Multidiffusion

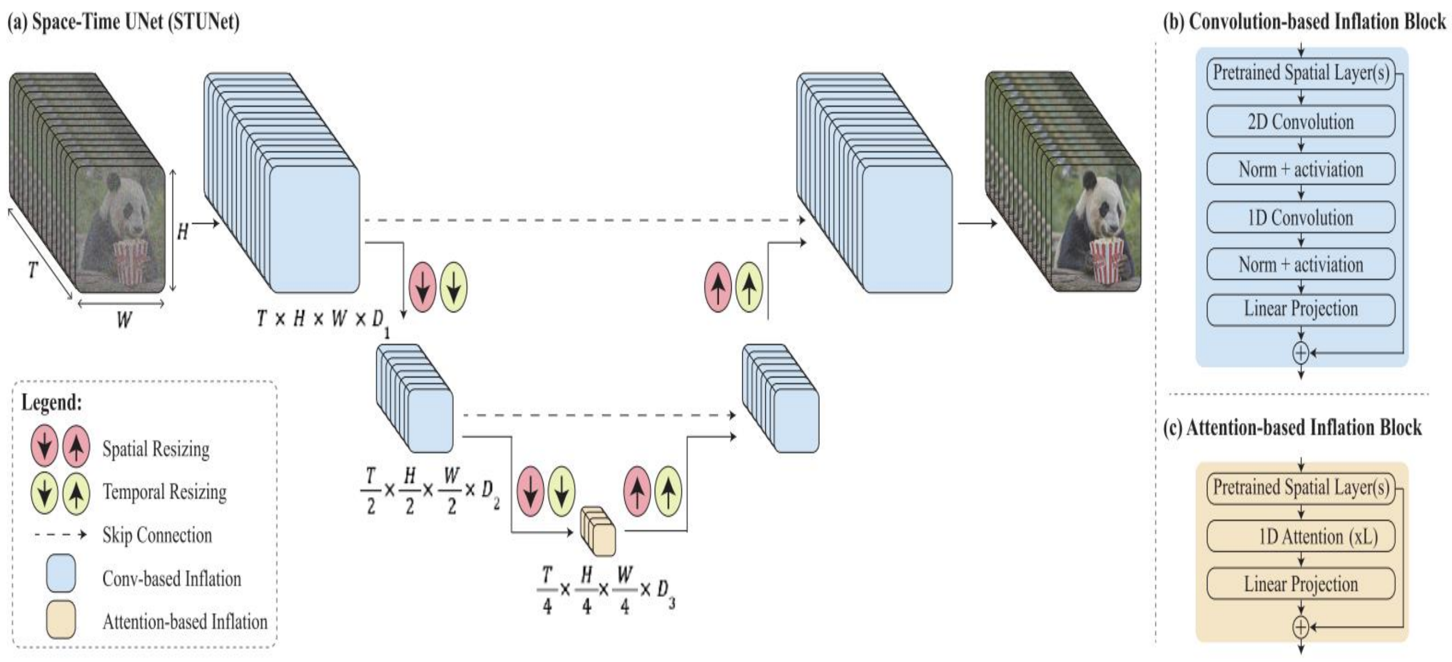
Lumiere: A Space-Time Diffusion Model for Video Generation, SIGGRAPH 2024, https://arxiv.org/pdf/2401.12945

Method - STUnet



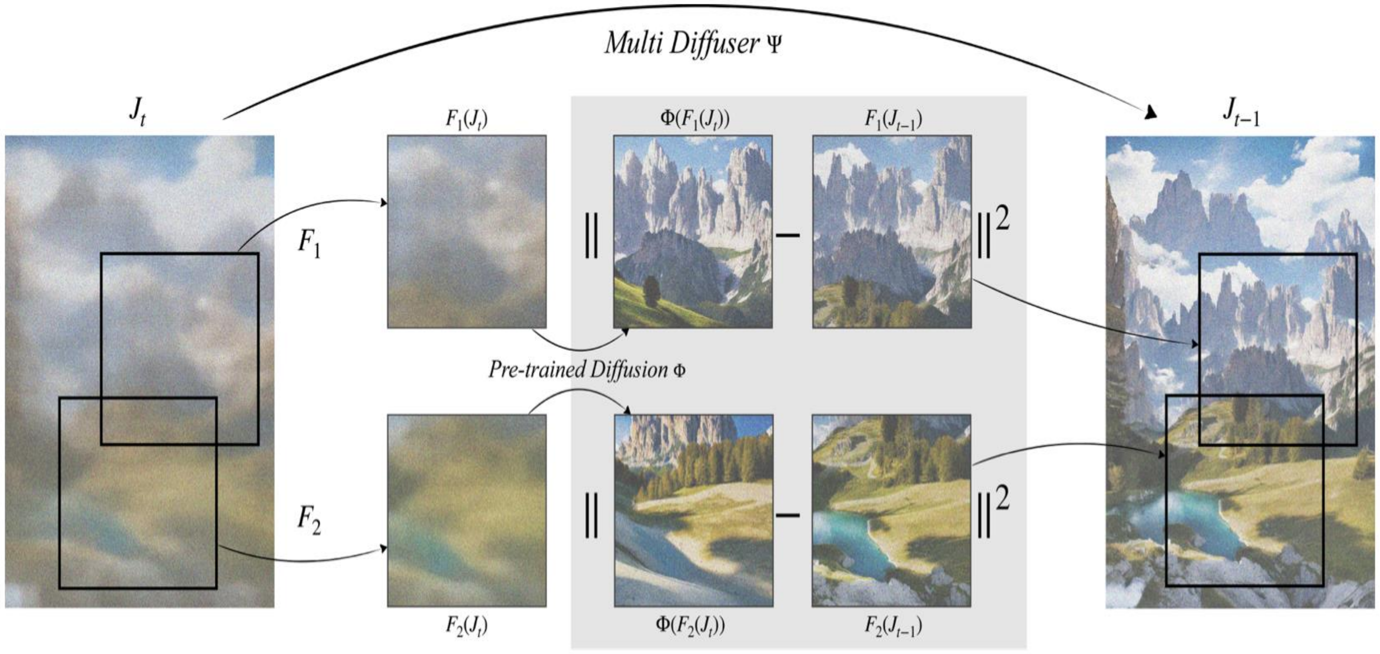
Employs traditional U-Net Model

Method - STUnet



- Interleave temporal blocks to T2I Architecture
- Trains only new parameters
- Performs identity Initialization
- Low computational Overhead

Method - Multidiffusion



Multidiffusion Framework:

- New generation process from a pre-trained model
- Fuses inconsistent directions into one global denoising step

MultiDiffusion: Fusing Diffusion Paths for Controlled Image Generation, ICML 2023, https://arxiv.org/pdf/2302.08113

SSR with Multidiffusion

- An inflated SSR network can only operate on short videos
- Employ multidiffusion for smooth temporal transition
- Multidiffusion prevents temporal artifacts
  - Resolved by linearly combining video segments

SSR with Multidiffusion

- At each generation step:
  - split noisy input video $J \in \mathbb{R}^{H \times W \times T \times 3}$ into $1 \dots N$ overlapping segments
  - Where $J_i \in \mathbb{R}^{H \times W \times T' \times 3}$ is the i^{th} segment
  - Temporal duration: $T' < T$

- To reconcile per-segment SSR predictions:

$$\arg\min_{J'} \sum_{i=1}^{n} \left\| J' - \Phi(J_i) \right\|^2 .$$

Evaluation Setup

- Train T2V model on 30M videos with text prompts
  - Videos are 80 frames long at 16 fps
  - 109 text prompts
  - Base model dimension: 128 x 128 frames
  - SSR dimension: 1024 x 1024 frames

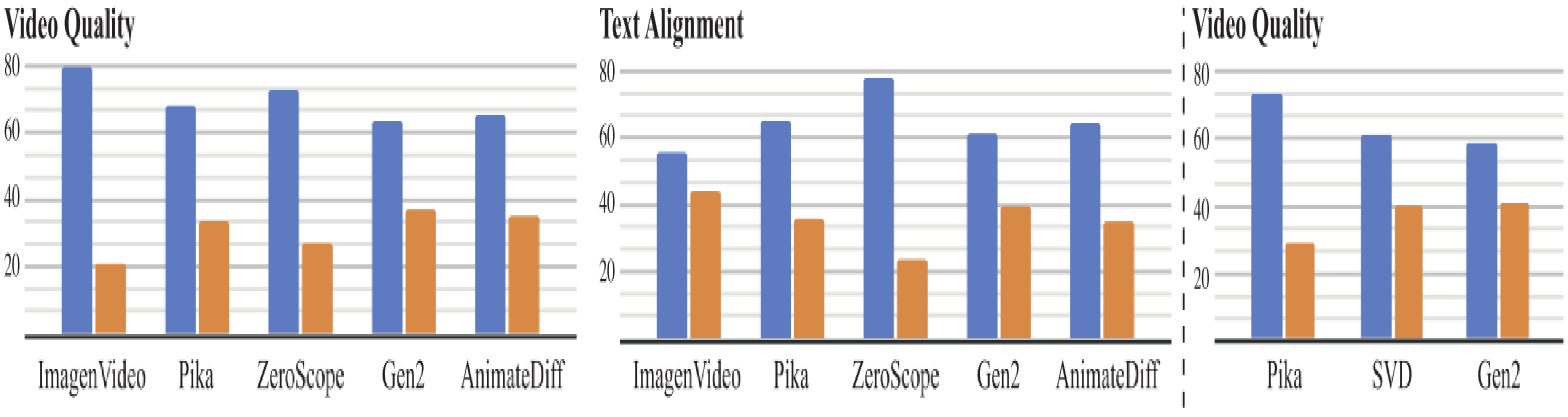
Zero-shot on UCF-101

Method	FVD ↓	IS ↑
MagicVideo (Zhou et al., 2022)	655.00	-
Emu Video (Girdhar et al., 2023)	606.20	42.70
Video LDM (Blattmann et al., 2023b)	550.61	33.45
Show-1 (Zhang et al., 2023a)	394.46	35.42
Make-A-Video (Singer et al., 2022)	367.23	33.00
PYoCo (Ge et al., 2023)	355.19	47.76
SVD (Blattmann et al., 2023a)	242.02	-
Lumiere (Ours)	332.49	37.54

User Study

- Two-alternative Forced Choice protocol Adopted
  - Randomly ordered pairs of videos are provided
  - 400 user judgments obtained
  - 109 prompts were utilized
  - Fixed random seed
  - Spatial and Temporal alignment

User Study



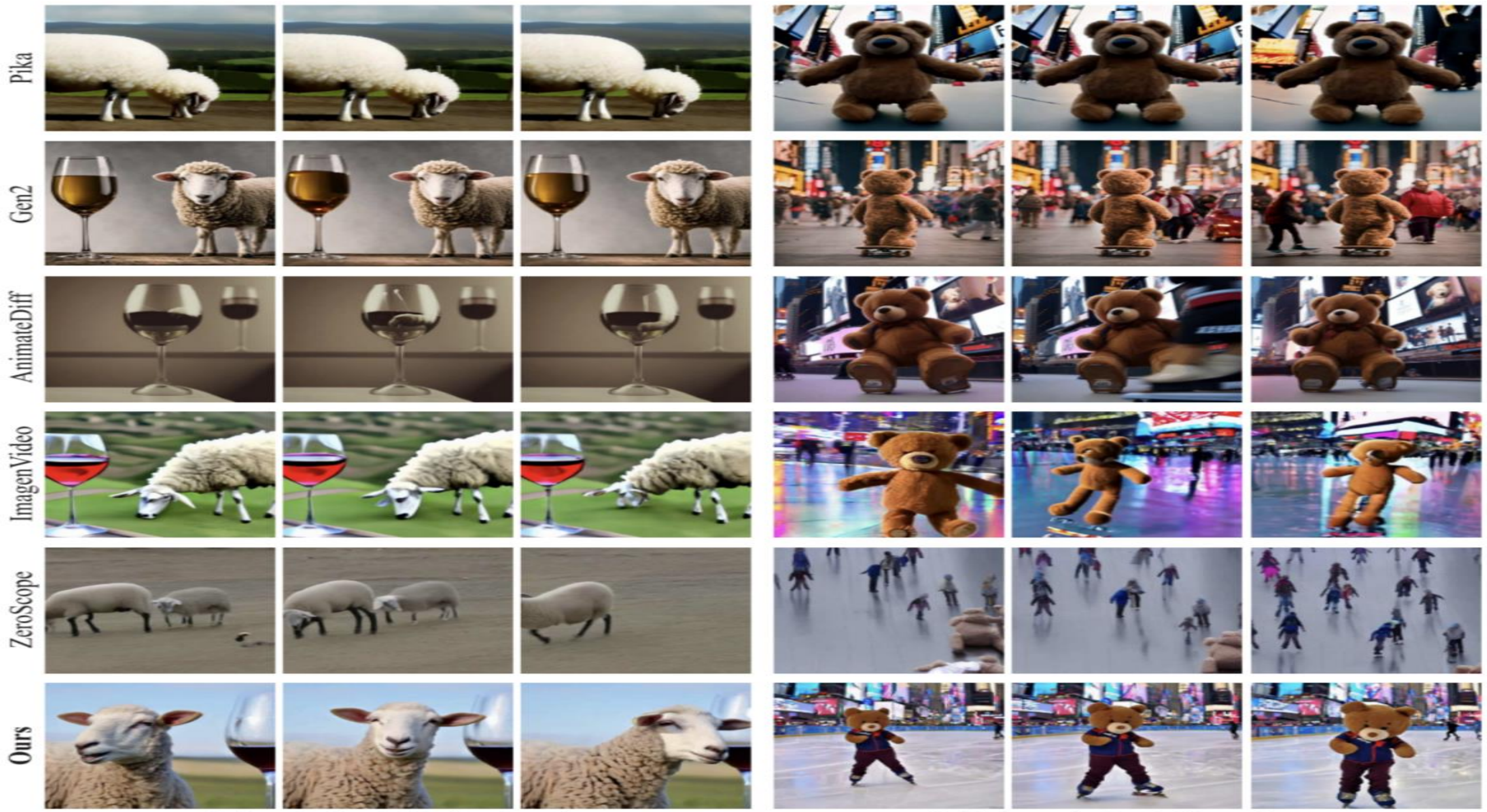
(a) Text-to-Video

(b) Image-to-Video

User Study

Left video | Right video

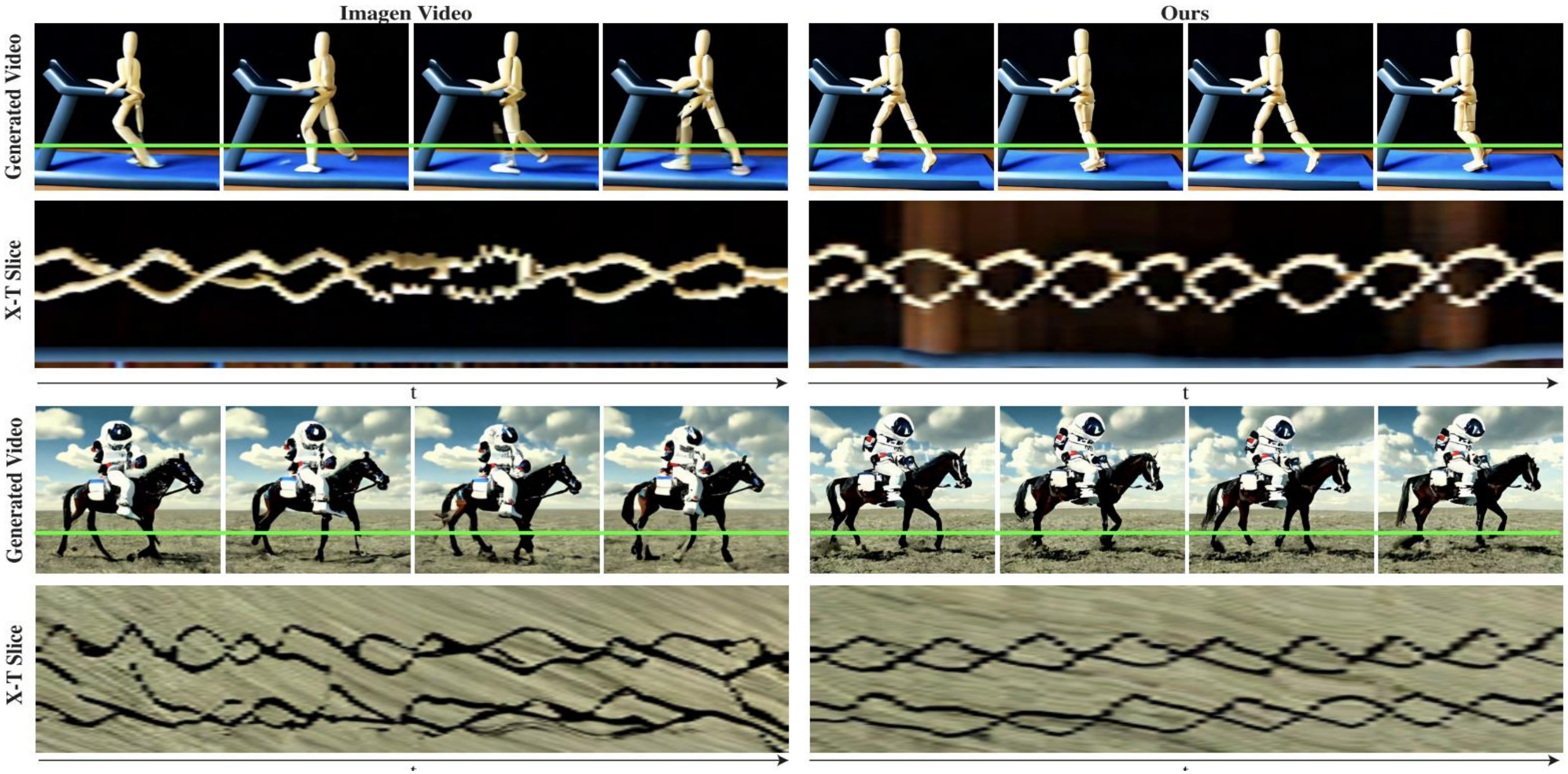
Qualitative Evaluation



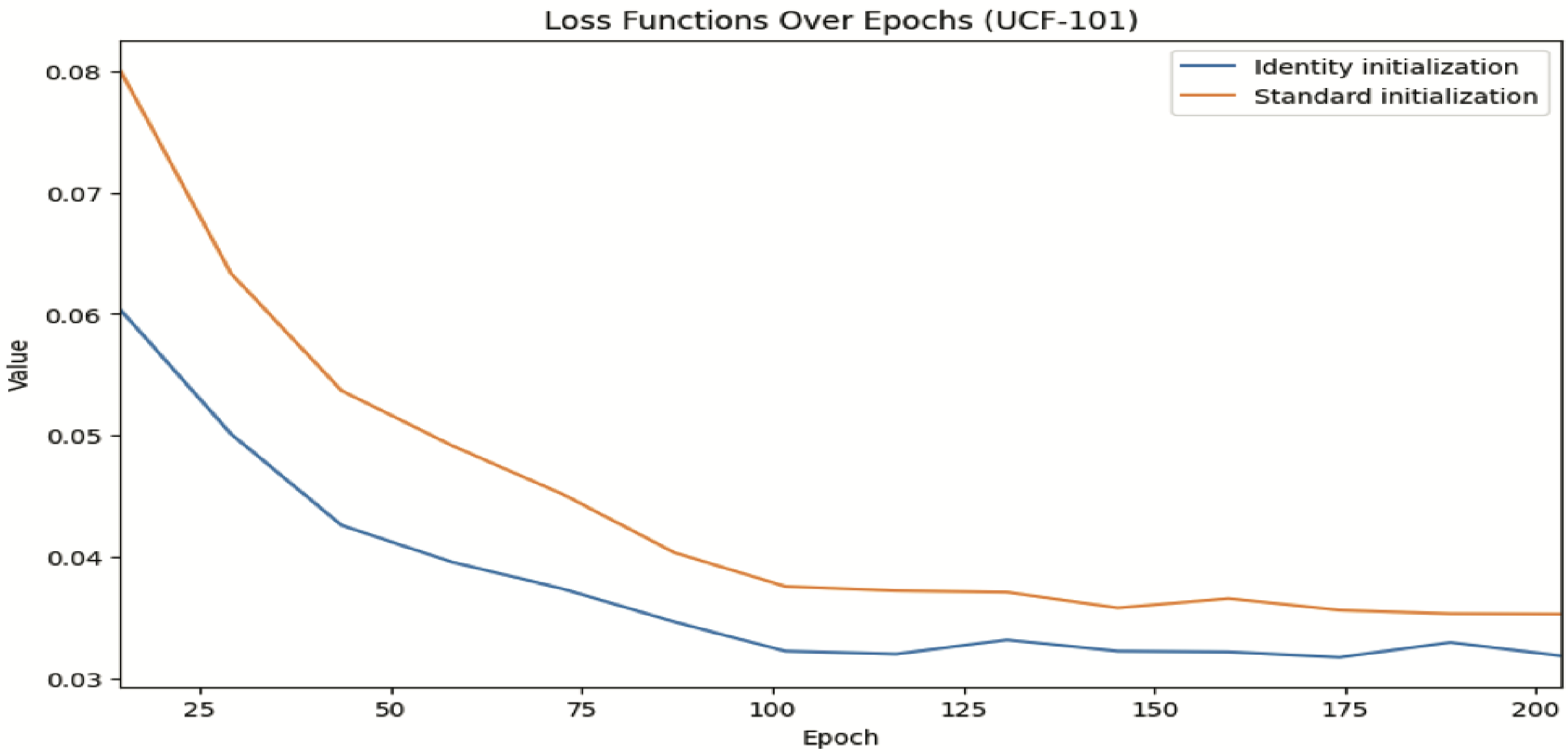
A sheep to the right of a wine glass

Teddy bear skating in Times Square

Temporal Consistency

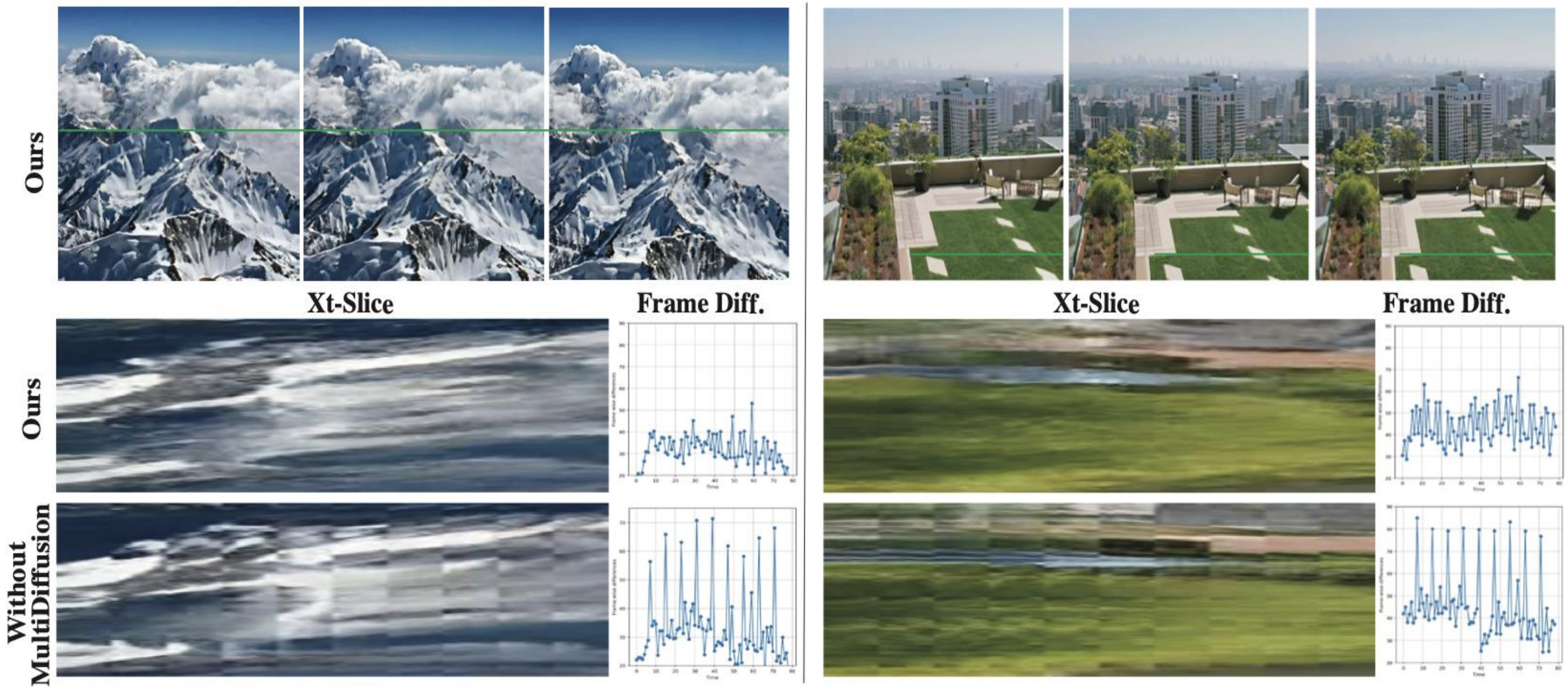


Ablation - Initialization

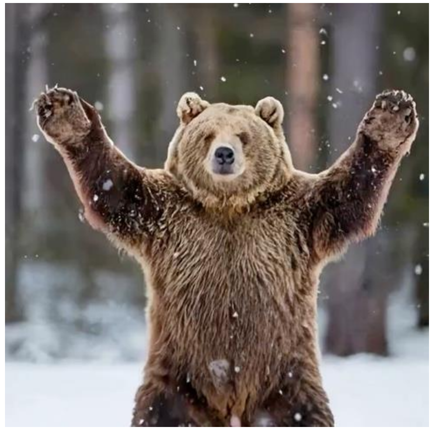


Visualize Initialization Schemes

Ablation - Multidiffusion



Applications – Video Editing



Original Video

Generated Video

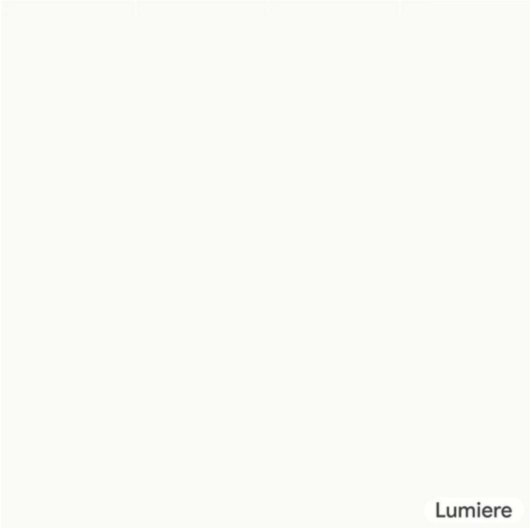
SDEDIT: GUIDED IMAGE SYNTHESIS AND EDITING WITH STOCHASTIC DIFFERENTIAL EQUATIONS, Jan 2022, https://arxiv.org/pdf/2108.01073

Application – Stylized Generation

- Pre-trained T2I weights remain fixed
- Newly added temporal layers are trained
- Linear interpolation between fixed and fine-tuned T2I weights
  - $W_{interpolate} = \alpha \cdot W_{style} + (1 - \alpha) \cdot W_{orig}$
  - Where $\alpha \in [0.5, 1]$

Application – Stylized Generation

Vector art styles

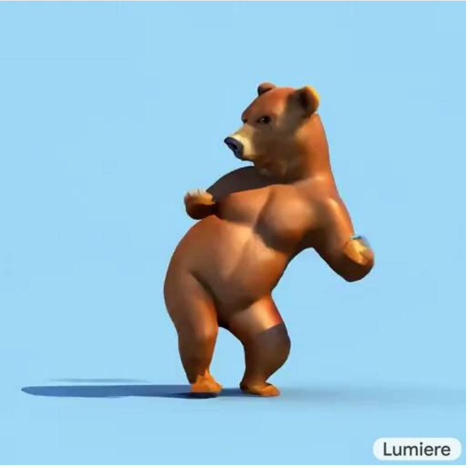


Reference Image

Output

Application – Stylized Generation

Realistic styles



Reference Image

Output

Application – Conditional Generation

- Model conditioned on additional input signals
  - Noisy video $J \in \mathbb{R}^{H \times W \times T \times 3}$
  - Text prompt
  - Masked conditioning video $C \in \mathbb{R}^{H \times W \times T \times 3}$
  - Binary Mask $M \in \mathbb{R}^{H \times W \times T \times 1}$

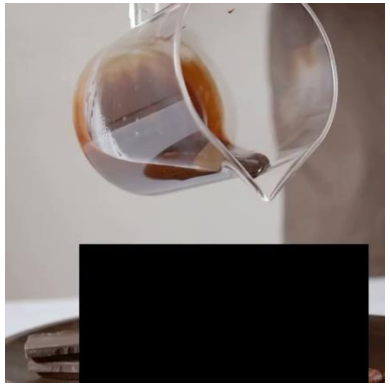
- Concatenated Tensor $\langle J, C, M \rangle = \mathbb{R}^{T \times H \times W \times 7}$

Application – Image to Video

Application - Inpainting

Video + Mask

Output



Application - Cinemagraphs

Source Image + Mask

Output

Societal Impact

- Risk of misuse
  - Tools for detecting biases and malicious use cases
  - To ensure safe and fair use

Limitations

- The model cannot generate videos
  - Multiple shots
  - Transition between scenes
- The model operates in pixel space

Conclusion

- Presents a novel T2V framework
  - Built on a pre-trained T2I model
  - Introduces space-time U-Net Architecture
  - Utilizes Multidiffusion framework
- Demonstrates state-of-the-art generation results
- Showcases applicability to various downstream tasks

Thank you