Lumiere: A Space-Time Diffusion Model for Video Generation

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SIGGRAPH 2024, 259 citations

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UCF

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

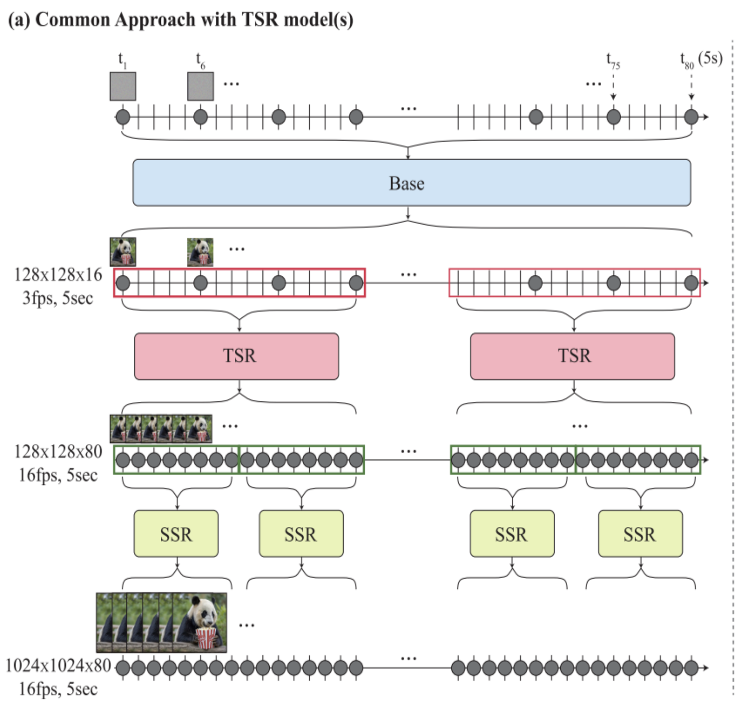
Motivation

- 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

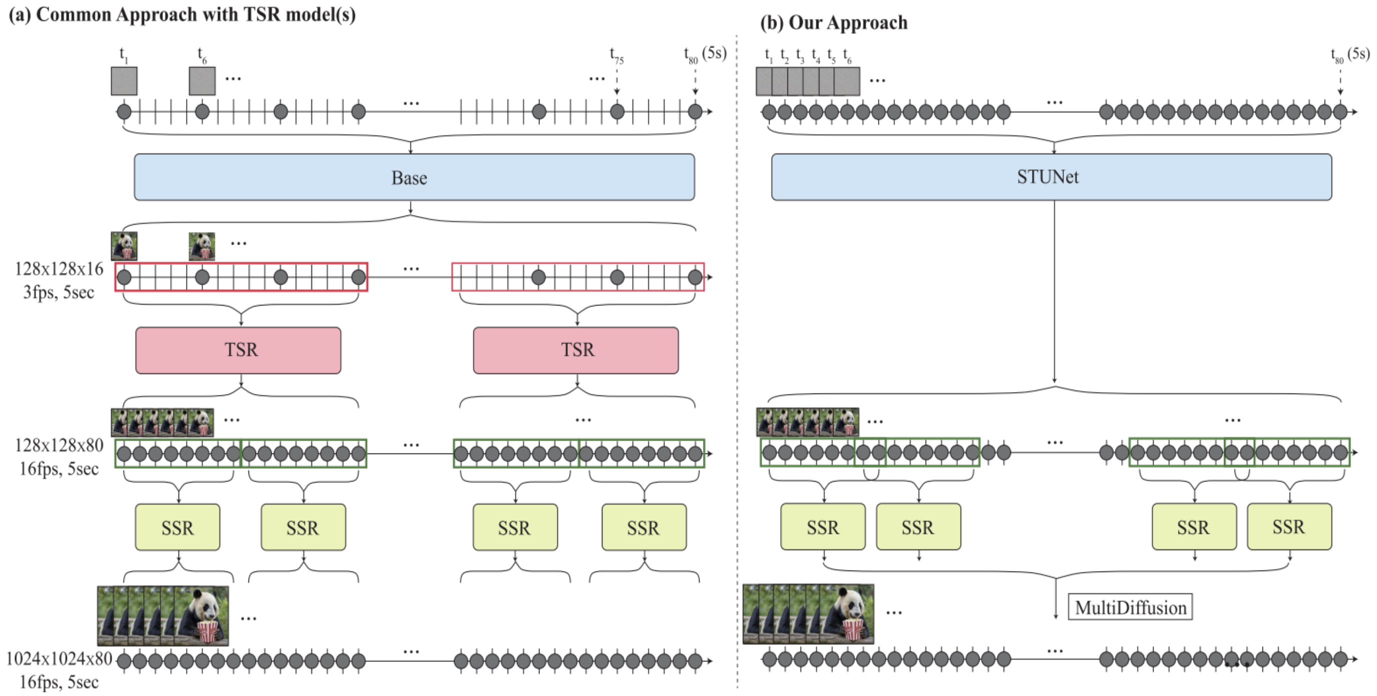
Method - Pipeline



Common T2V Framework:

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

Method - Pipeline

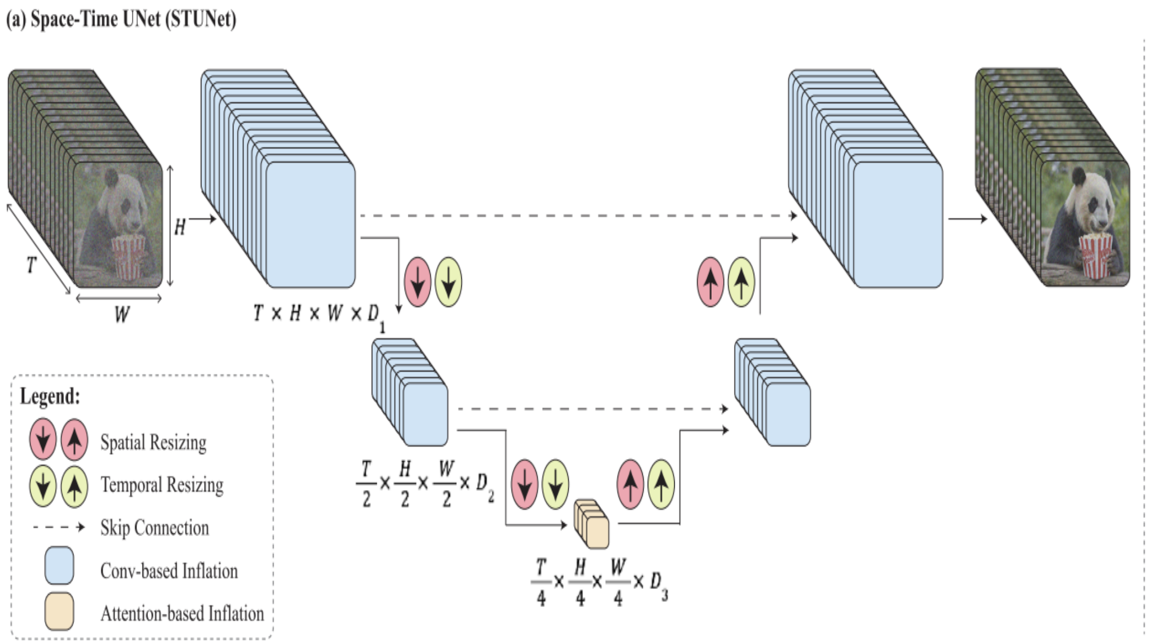


Lumiere Framework:

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

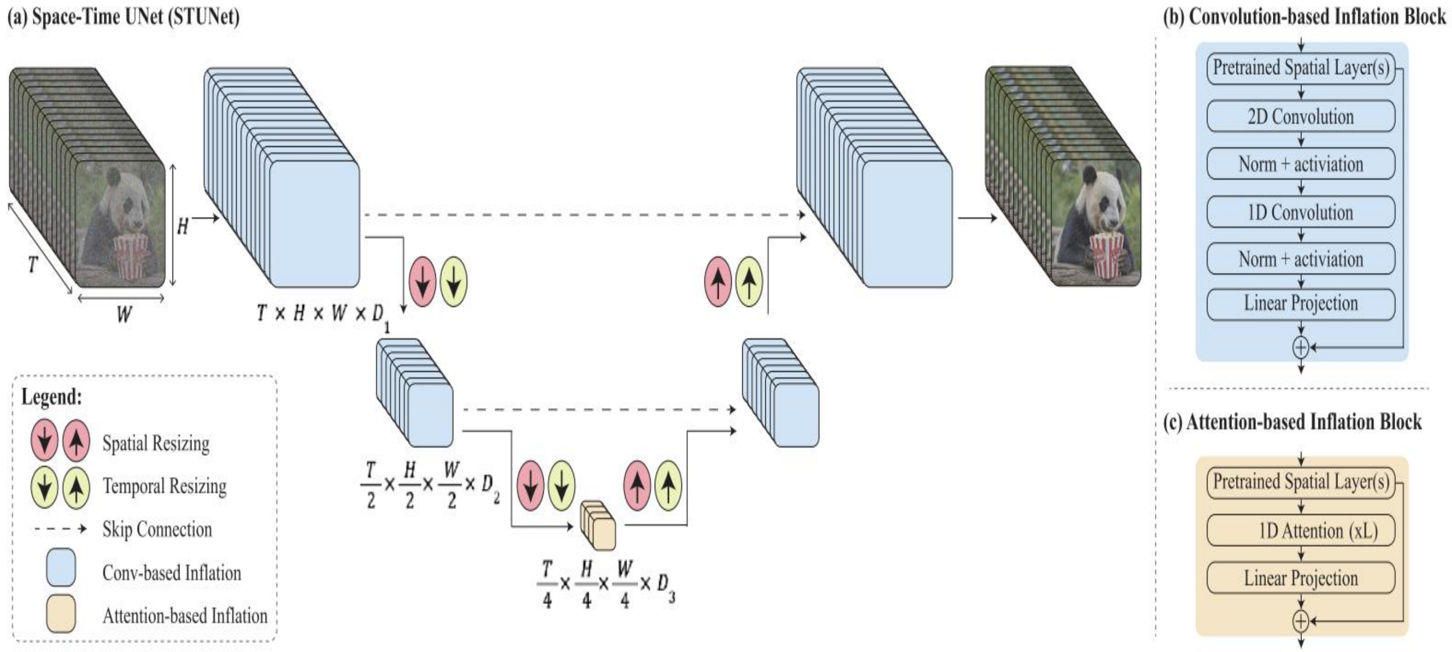
Lumiere: A Space-Time Diffusion Model for Video Generation, SIGGRAPH 2024, https://arxiv.org/pdf/2401.12945

Method - STUnet



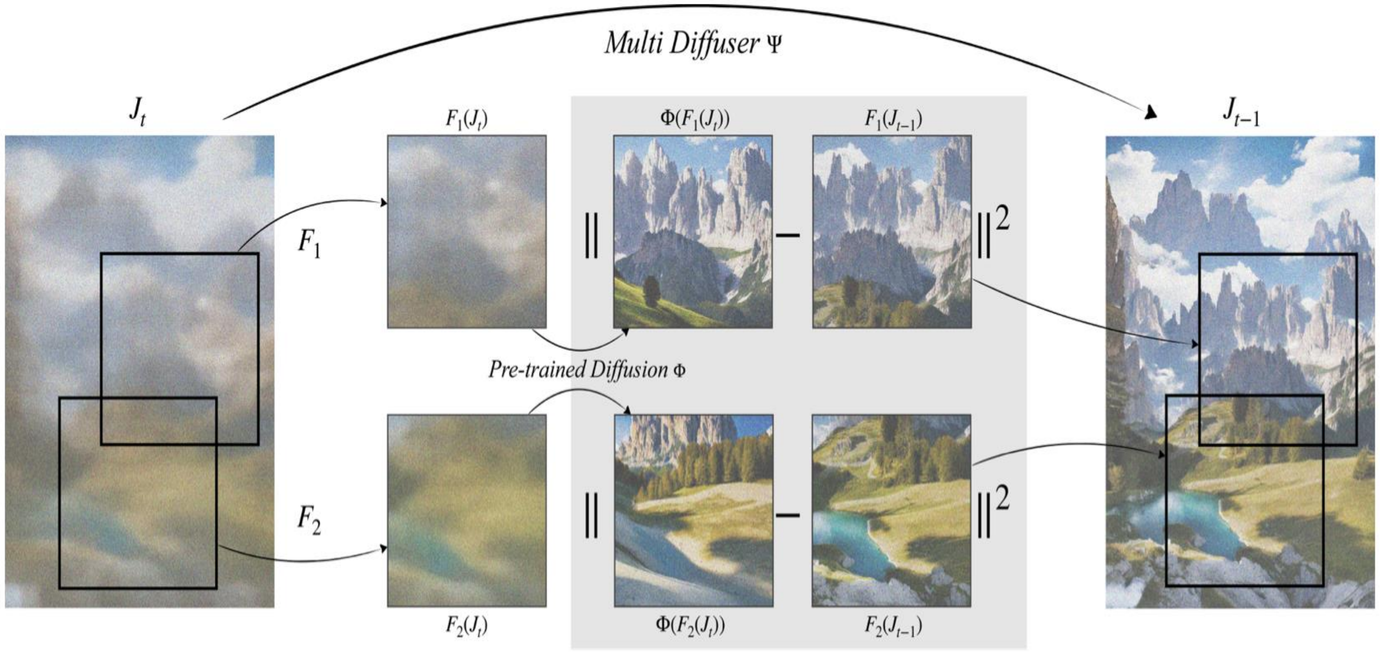
Employs traditional U-Net Model

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 $1 \ldots N$ 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

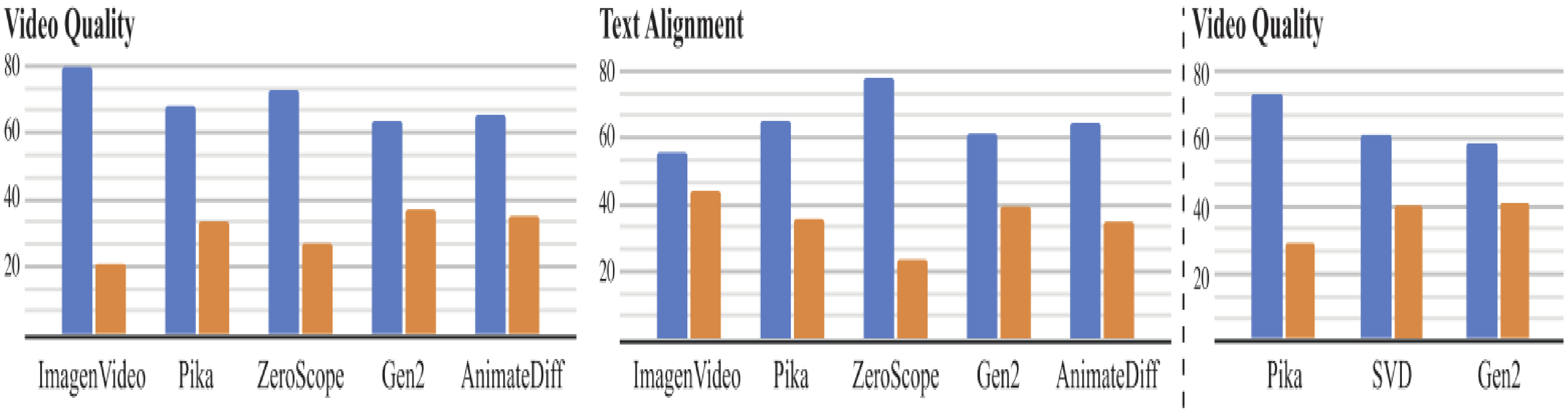
Zero-shot on UCF-101

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

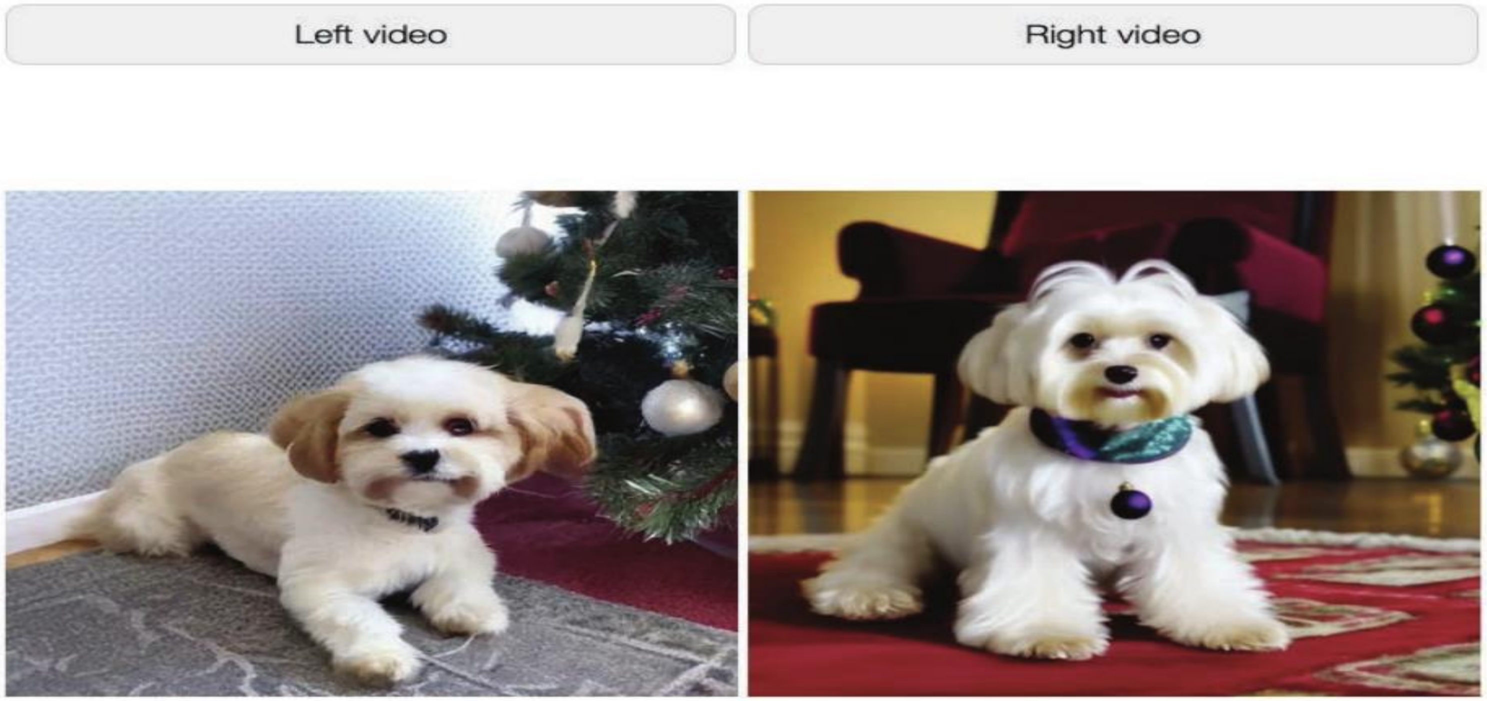
- Two-alternative Forced Choice protocol Adopted
  - Randomly ordered pairs of videos are provided
  - 400 user judgments obtained
  - 109 prompts were utilized
  - Fixed random seed
  - Spatial and Temporal alignment

User Study

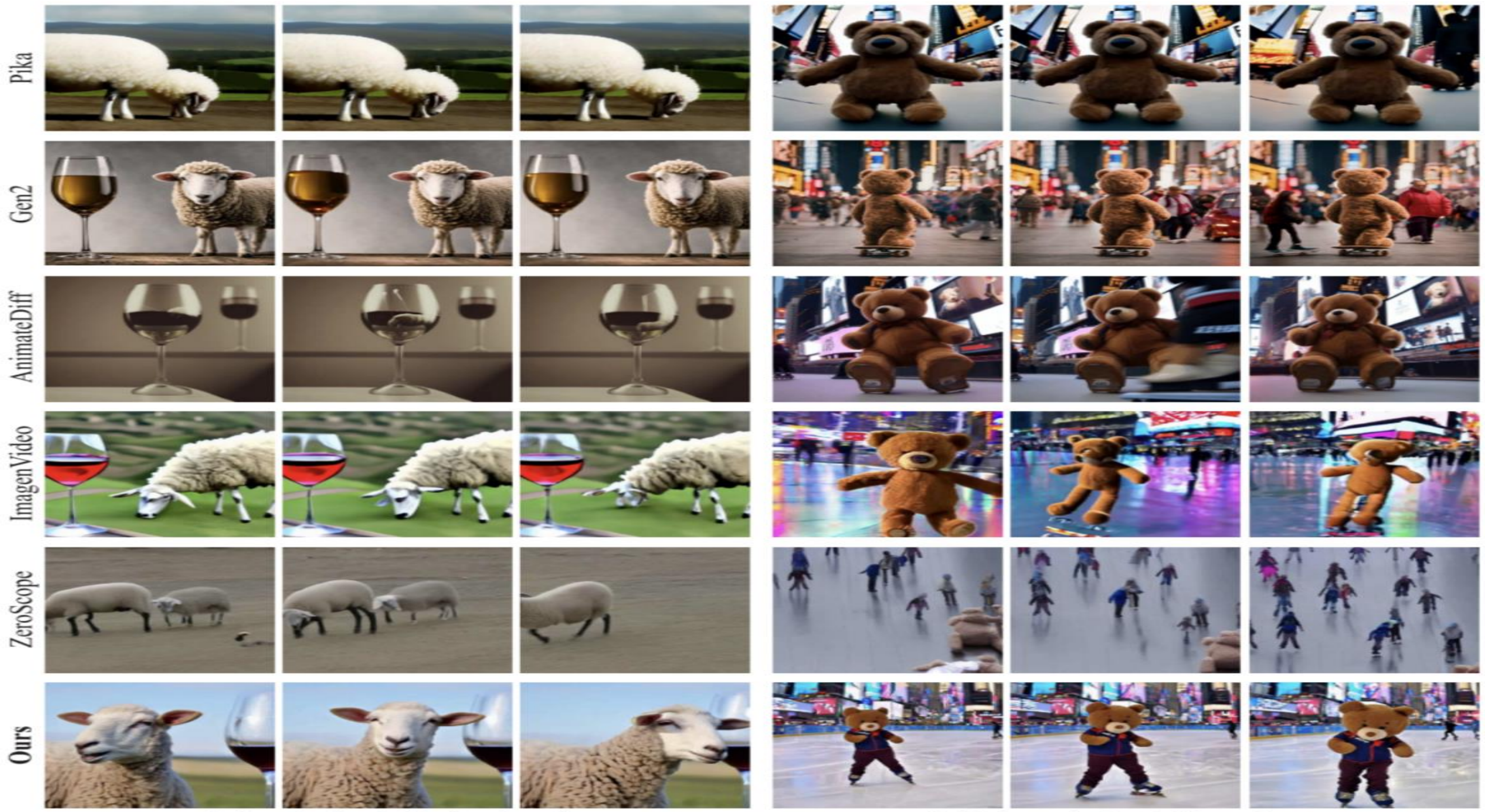


(a) Text-to-Video (b) Image-to-Video

User Study



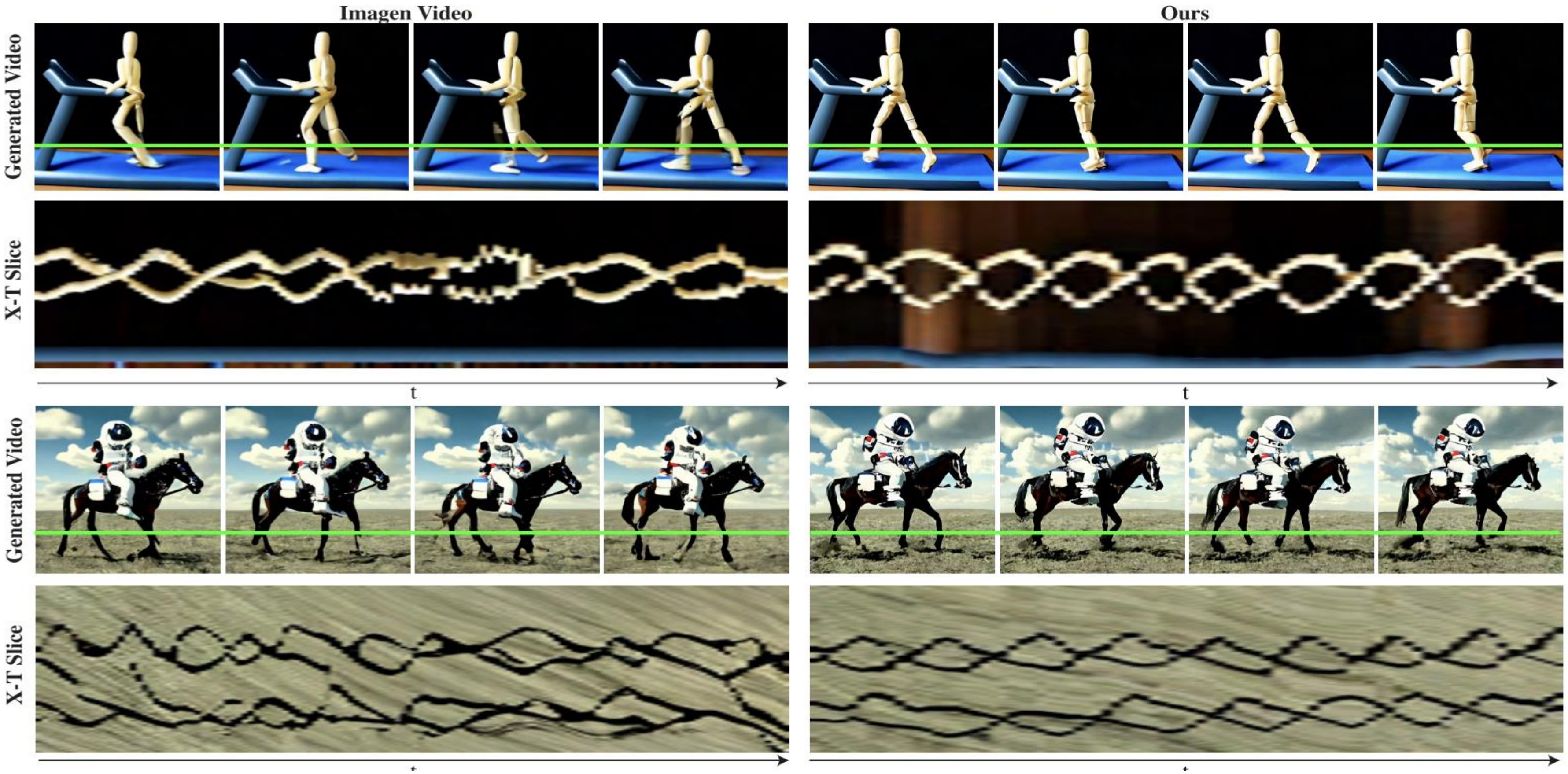
Qualitative Evaluation



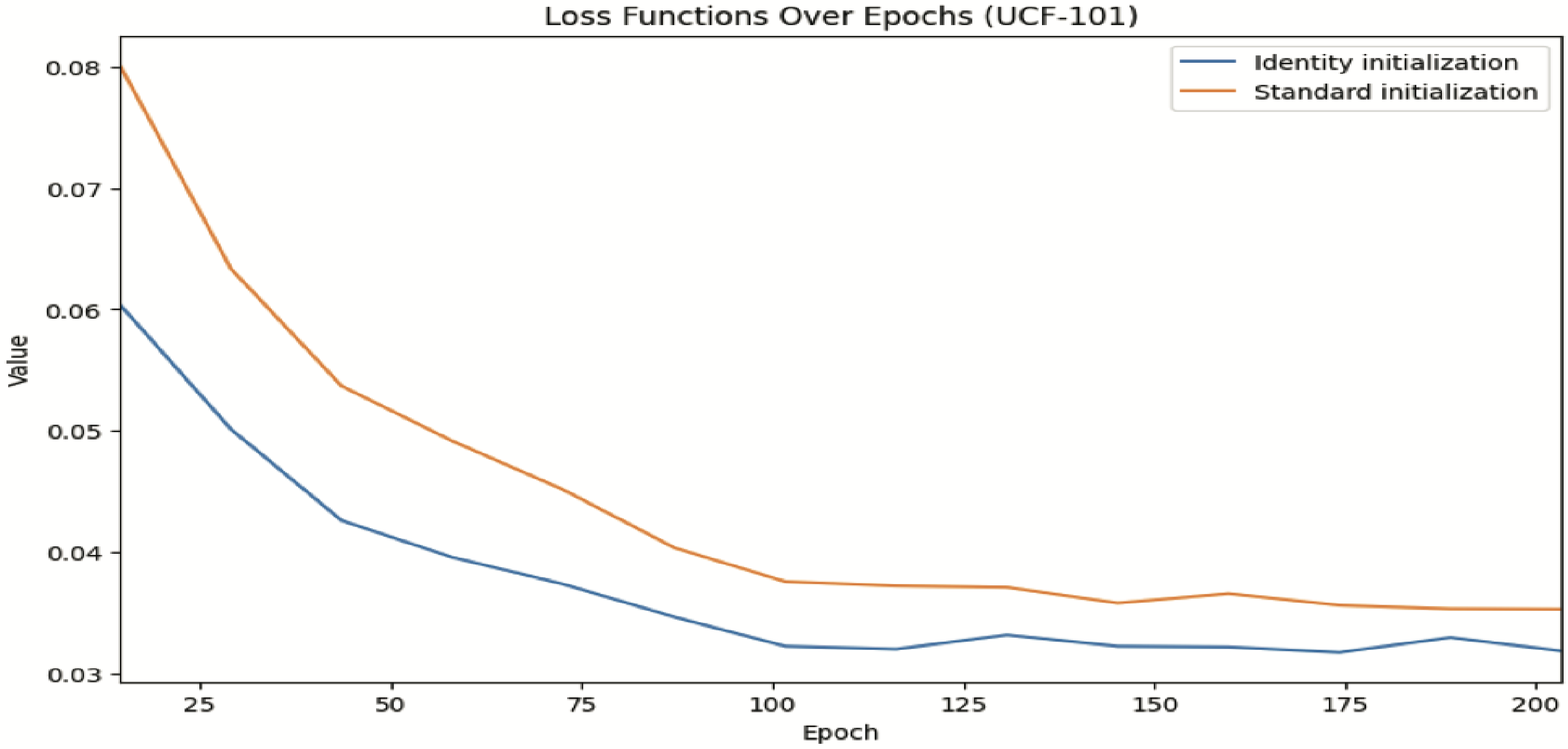
A sheep to the right of a wine glass

Teddy bear skating in Times Square

Temporal Consistency

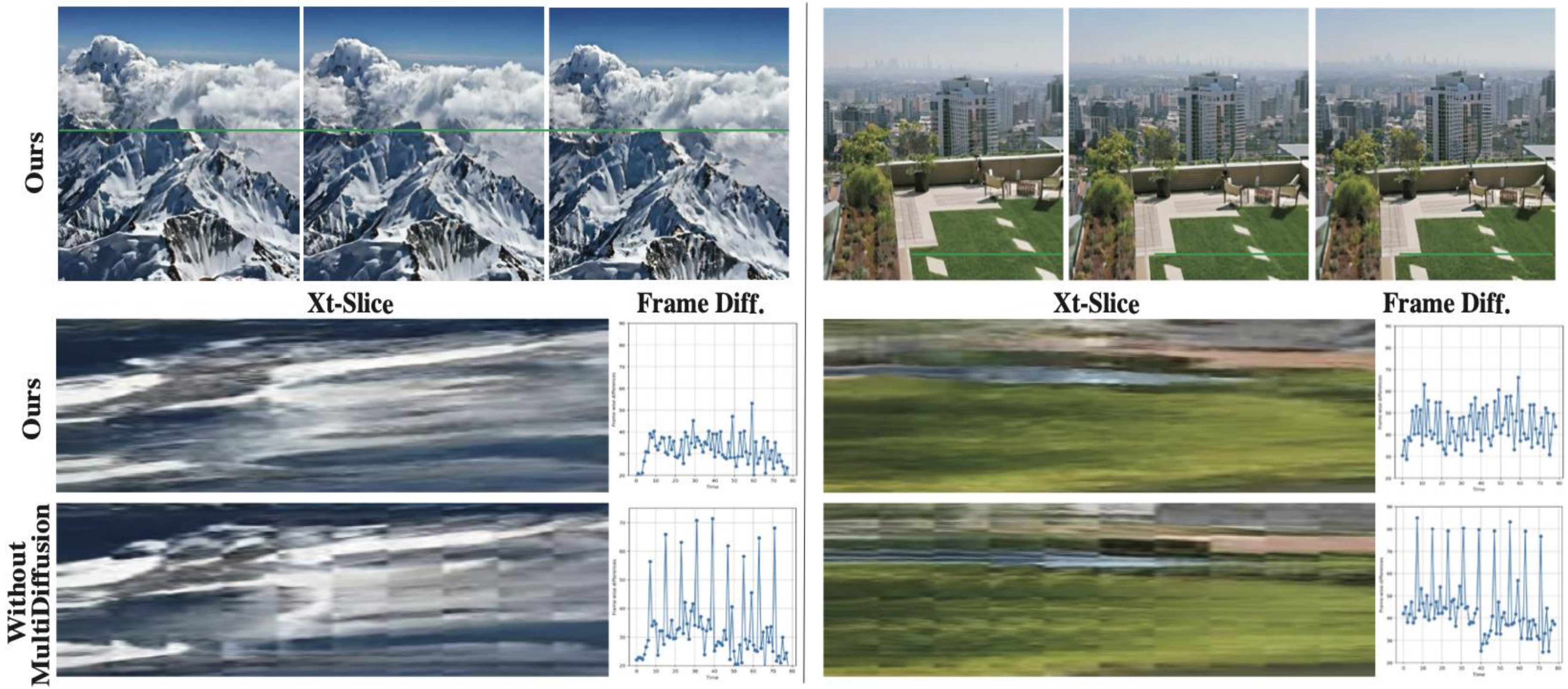


Ablation - Initialization

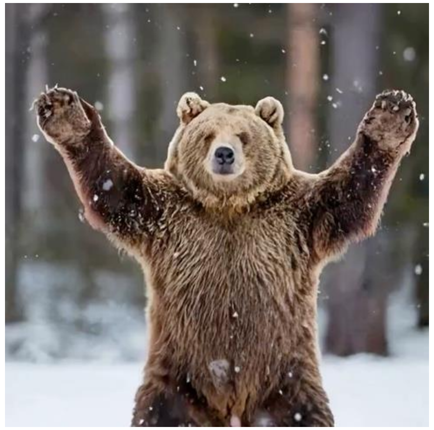


Visualize Initialization Schemes

Ablation - Multidiffusion



Applications – Video Editing



Original Video

Generated Video

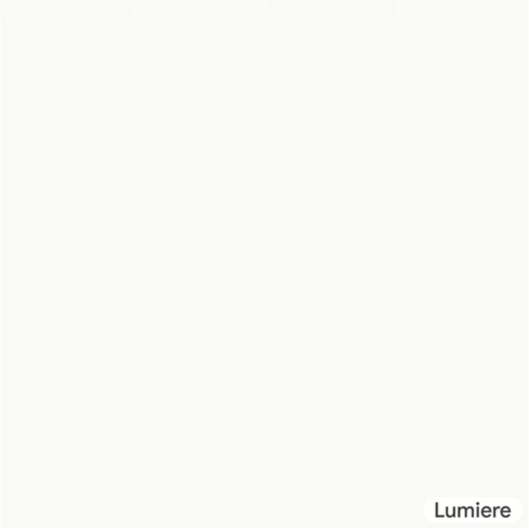
SDEDIT: GUIDED IMAGE SYNTHESIS AND EDITING WITH STOCHASTIC DIFFERENTIAL EQUATIONS, Jan 2022, https://arxiv.org/pdf/2108.01073

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

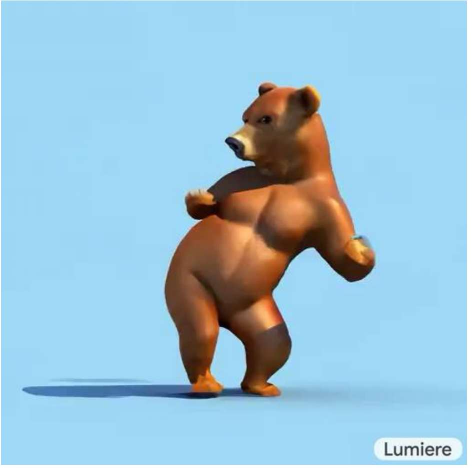


Reference Image

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 $M \in \mathbb{R}^{H \times W \times T \times 1}$

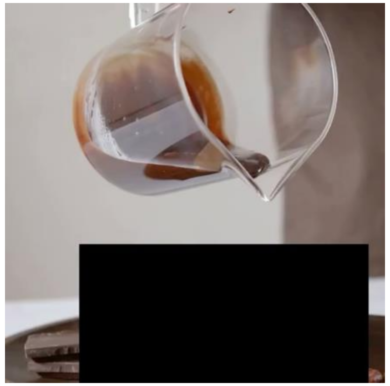
- Concatenated Tensor $\langle J, C, M \rangle = \mathbb{R}^{T \times H \times W \times 7}$

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