ICLR

A Good Image Generator Is What You Need For High-Resolution Video Synthesis

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Video Synthesis: Background

- Video synthesis: Create *unseen* video clips from random noises

Random noise

Video Synthesis: Difficulties

- Lack of training data.
- Large Models, hard to train.
- High cost for data collection / training.

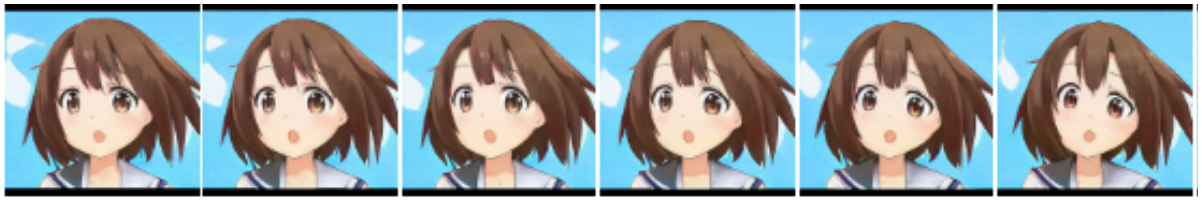
StyleGAN2[1]: 1024 resolution

TGANv2[2]: 256 resolution

[1] Analyzing and Improving the Image Quality of StyleGAN, CVPR 2020
[2]Train Sparsely, Generate Densely: Memory-efficient Unsupervised Training of High-resolution Temporal GAN, IJCV 2020

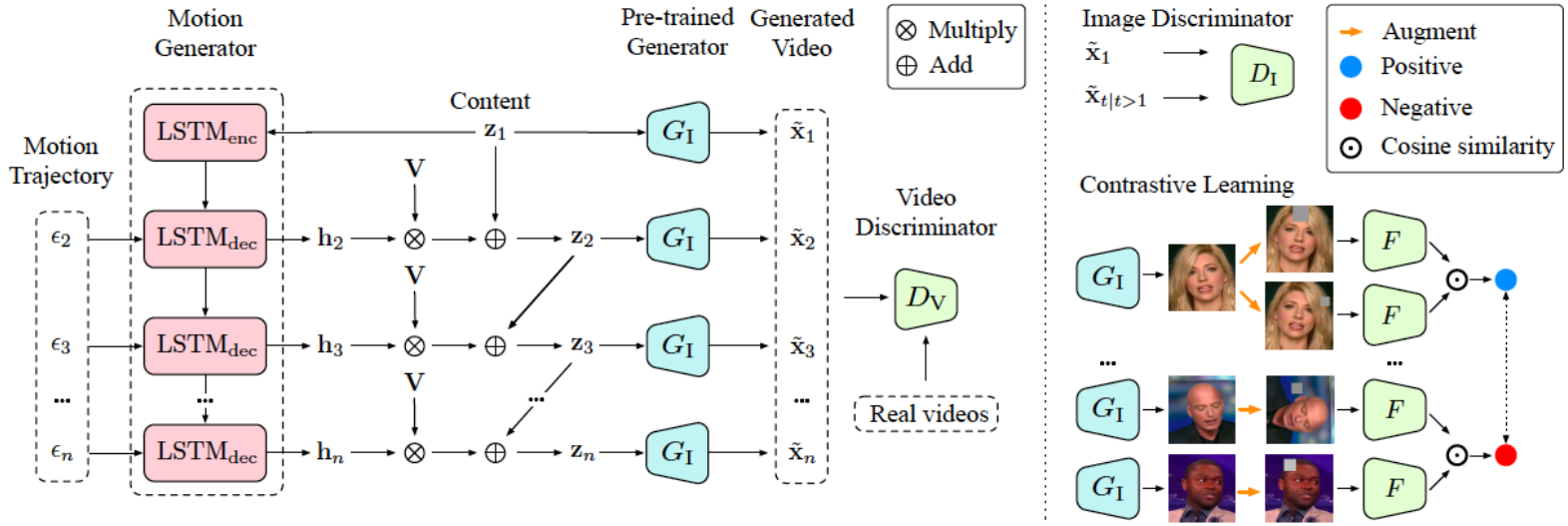
Methods: Intuition

- Reuse <u>pre-trained</u> image generator G_I in video synthesize training.
- Given image G_I: represent a video with a trajectory of random noises.



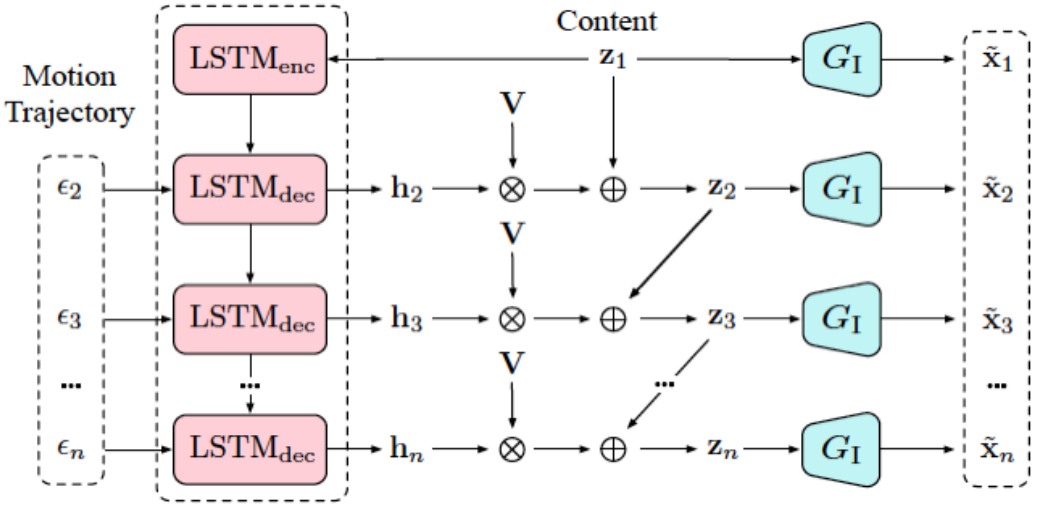
Methods: Framework

Motion generator (find trajectory) + Image generator (pre-trained, fixed) + 2D discriminator (content consistency) + 3D discriminator (motion)



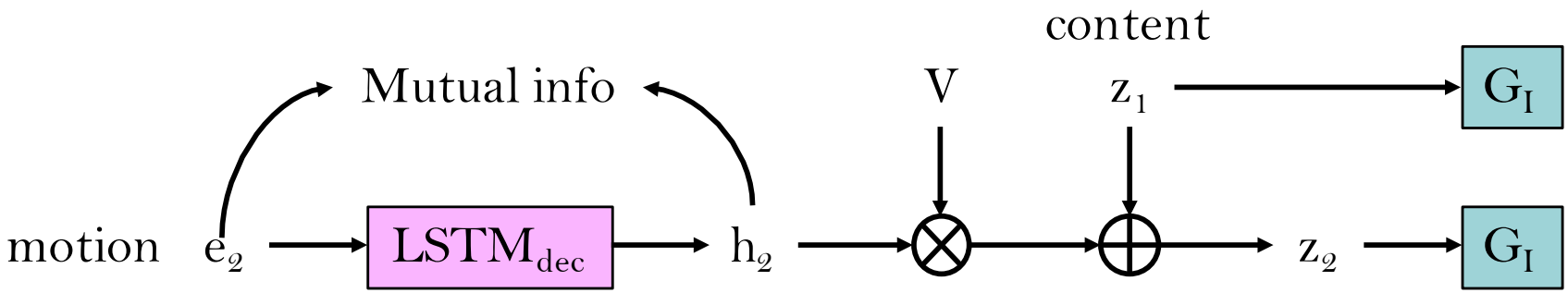
Methods: Motion Generator

- Motion generator: find the trajectory in the latent space of image generator
- LSTM *encoder* + LSTM *decoder*
- Estimate residual of previous frame → content/motion disentanglement



Motion Generator: Improve Diversity

- Mutual information loss: Maximize mutual info between e and h
- e ~ Gaussian: motion randomness
- h: output of LSTM decoder

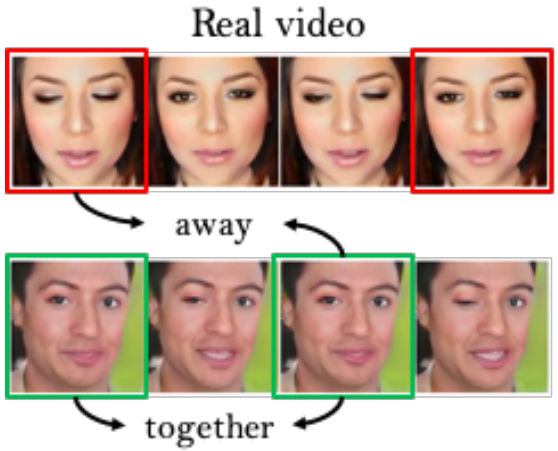


Methods: Image Generator

- Train image generator with video frames: in-domain video synthesis
- Use off-the-shelf image generator: cross-domain video synthesis
  - Cross-domain video synthesis: content from image dataset, motion from video dataset.
  - Save lots of **costs** in data collection: synthesis dog videos with dog images & human videos.

Methods: Contrastive 2D Discriminator

In-domain



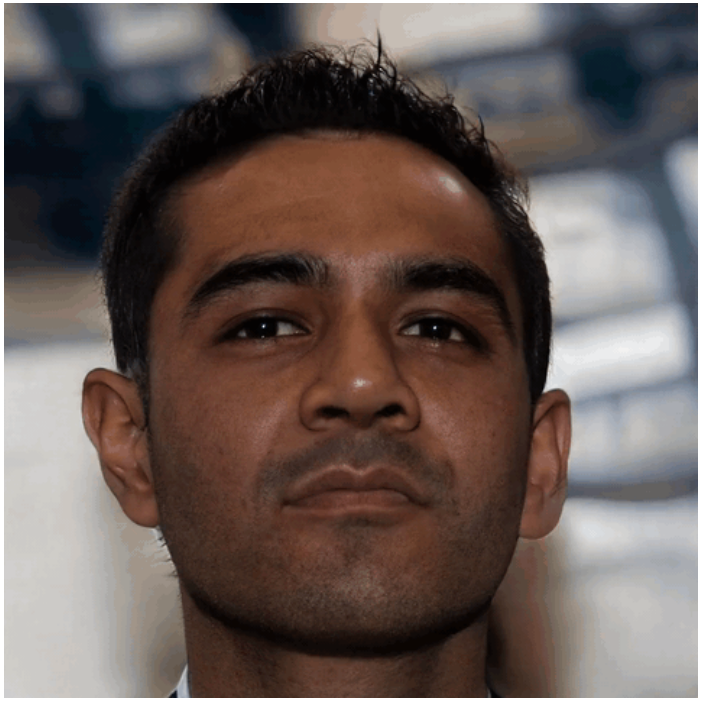
Cross-domain

Framework: Properties

- **High-resolution** video synthesis
- Motion/content **disentanglement**
- **Cross-domain** video synthesis
- **Long** sequence generation
- **Low** computation cost

Properties: High-resolution

Pre-trained image generator: 1024x1024

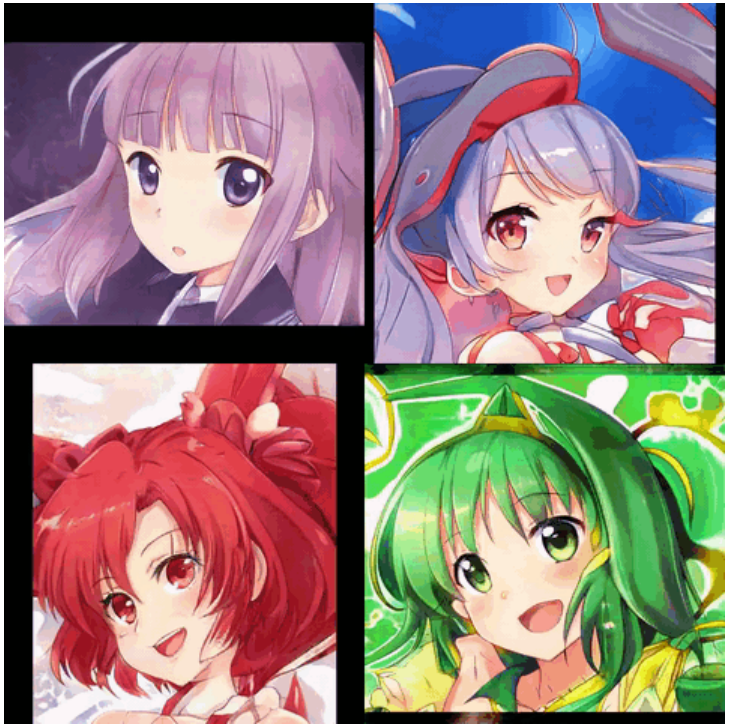


Properties: Motion/content Disentanglement

Residual design in motion generator

Properties: Cross-domain Video Synthesis

512 resolution, human face videos as training data



Properties: Cross-domain Video Synthesis

256 resolution, time-lapse videos as training data

Properties: Long Sequence Generation

(AFHQ, Vox): Interpolation

FaceForensics: LSTM unrolling

Properties: Low Computation Cost

- Pre-trained image generator:
  - **Small** batch-size for video training (as low as 8)
  - **Fixed** image generator: No gradient in video synthesis training

- Our models are trained with GPU (DVDGAN[1]: **TPU** only)
  - Save computation cost by **15 ~ 40X**

[1] Adversarial Video Generation on Complex Datasets, DeepMind 2019

Experiments: In-Domain (UCF-101)

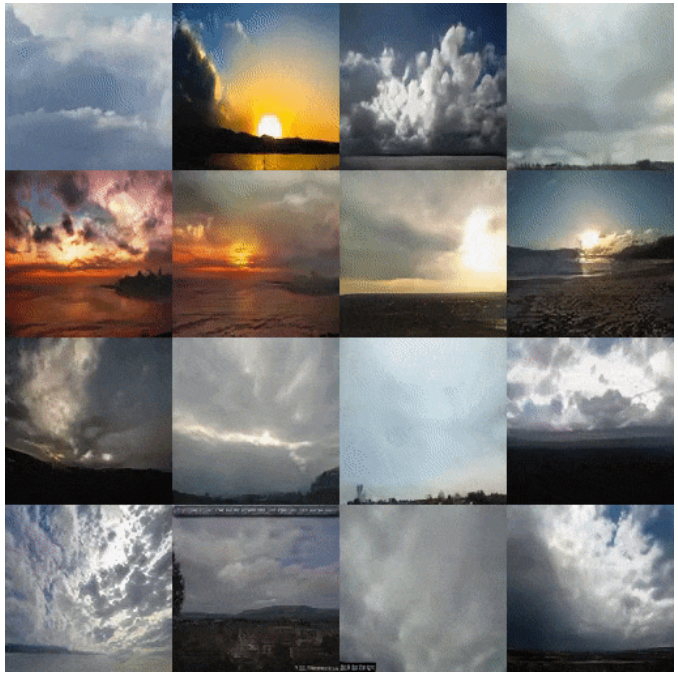
Method	IS (↑)	FVD (↓)
VGAN	8.31 ± .09	-
TGAN	11.85 ± .07	-
MoCoGAN	12.42 ± .07	-
ProgressiveVGAN	14.56 ± .05	-
TGANv2	26.60 ± .47	1209 ± 28
DVD-GAN	27.38 ± .53	-
Ours	**33.95 ± .25**	**700 ± 24**

Experiments: In-Domain (FaceForensics)

Method	FVD (↓)	ACD (↓)
GT	9.02	0.2935
TGANv2	58.03	0.4914
Ours	**53.26**	**0.3300**

[1] ACD from: MoCoGAN: Decomposing Motion and Content for Video Generation, CVPR 2018

Experiments: In-Domain (Sky Time-lapse)



Method	FVD (↓)	PSNR (↑)	SSIM (↑)
Up-B	-	25.367	0.781
MDGAN	840.95	13.840	0.581
DTVNet	451.14	21.953	0.531
Ours	**77.77**	**22.286**	**0.688**

Ablation: Mutual Info Loss

w/o mutual info loss

w/ mutual info loss

Ablation: Contrastive Loss

w/o contrastive discriminator

w/ contrastive discriminator

Summary

- Good image generator benefits video generation
  - LSTM motion generator + residual design
  - Pre-trained & fixed image generator
  - Contrastive 2D discriminator
  - Mutual information loss

- Code will be released at: https://github.com/snap-research/MoCoGAN-HD

Thanks!