Hierarchical Video Generation from Orthogonal Information: Optical flow and Texture

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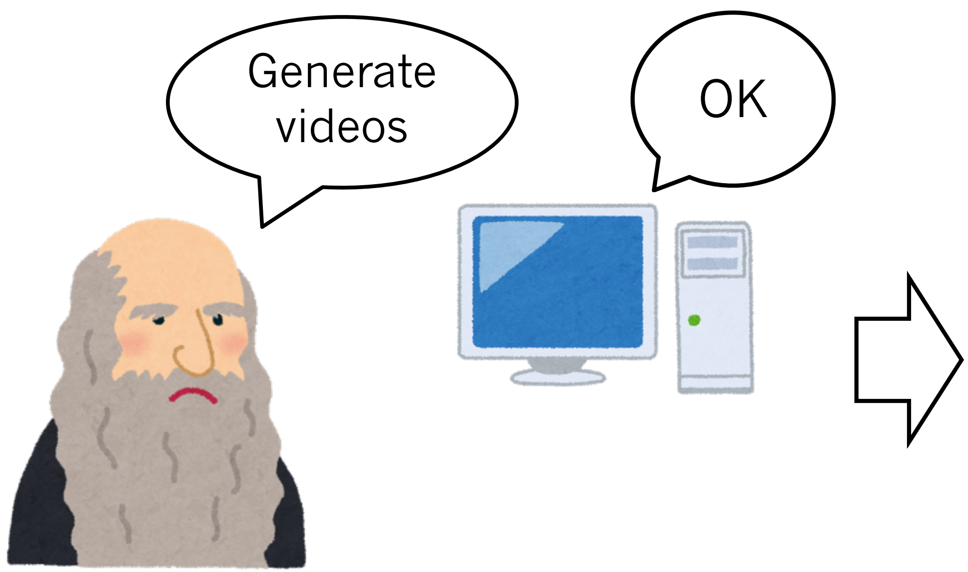
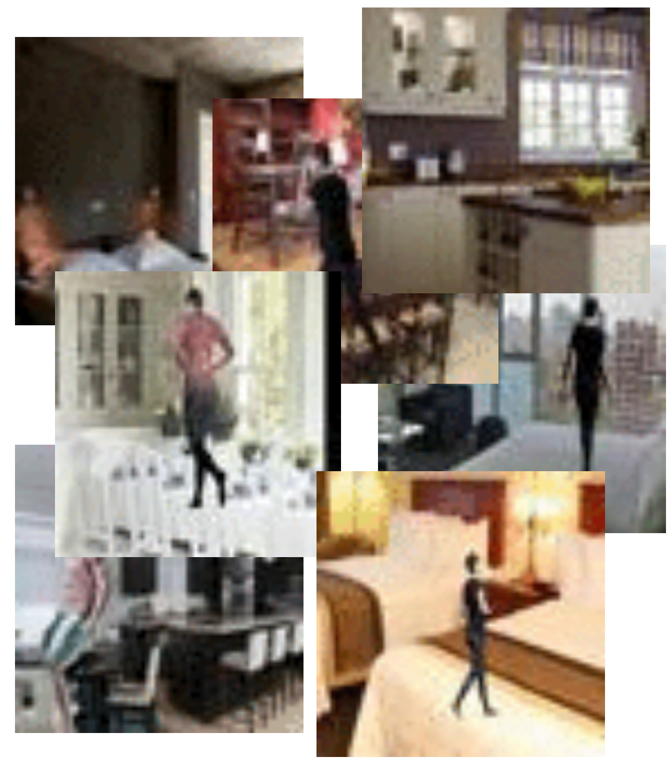
* indicates equal contribution.
§ currently belongs to DeNA Co., Ltd.

Paper&Slides: http://katsunoriohnishi.github.io/

Goal

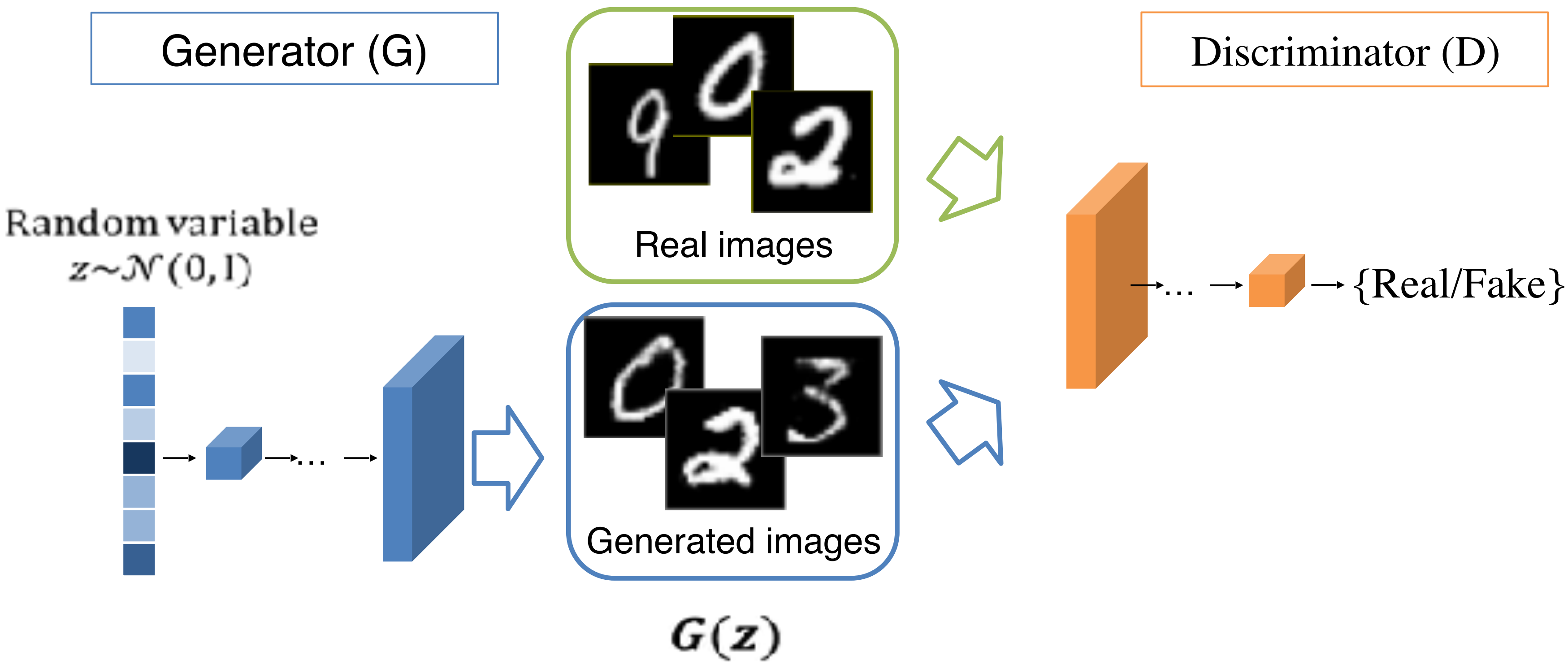
- Video generation
  - Applications)
    Human AI collaboration, dataset extension





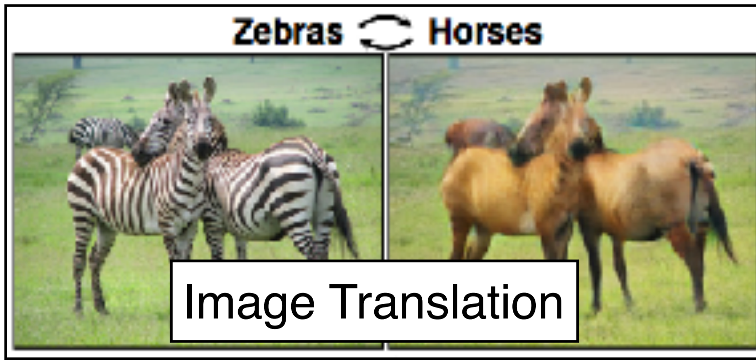
Generative Adversarial Network

- Generative Adversarial Network (GAN)
  [I. Goodfellow+, NIPS14]

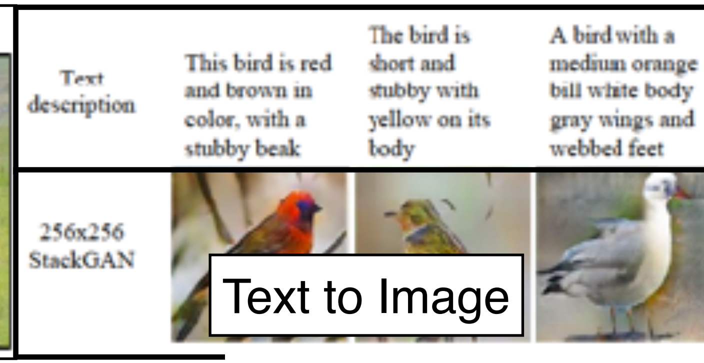


Generative Adversarial Networks

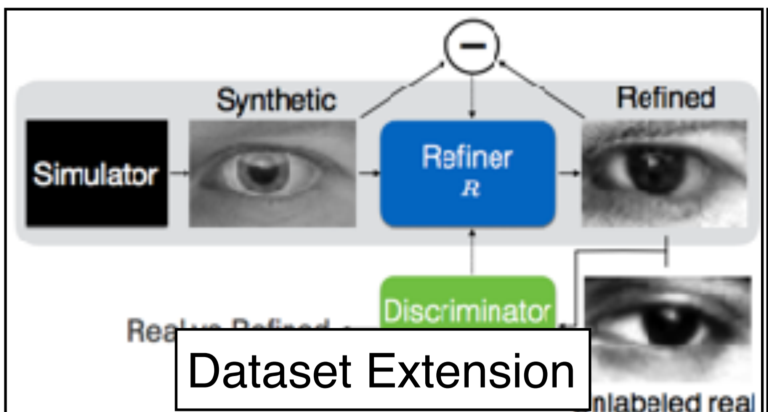
- Application



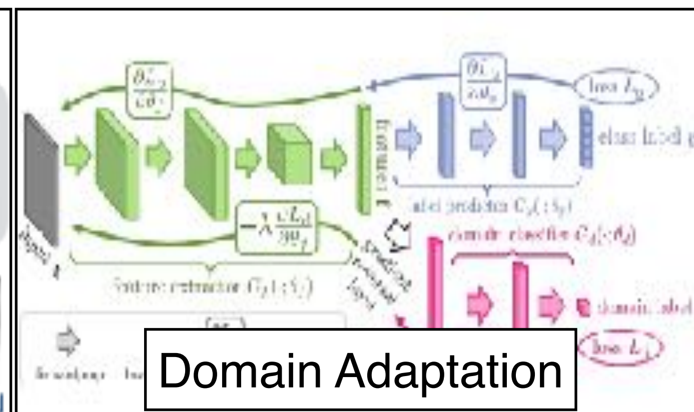
[JY Zhu, et al., ICCV17]



[H. Zhang, et al., ICCV17]



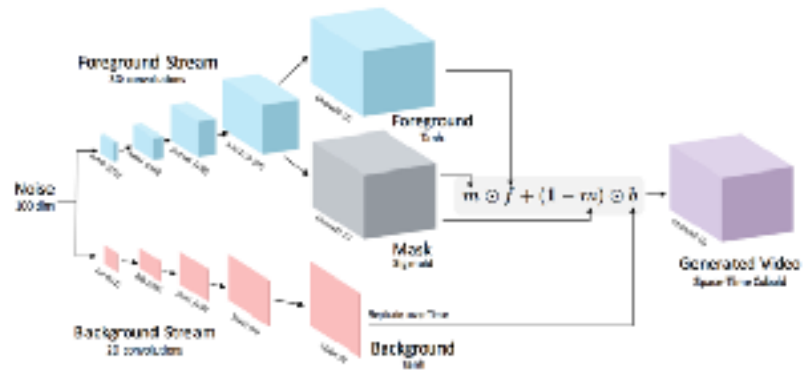
[A. Shrivastava, et al., CVPR17]



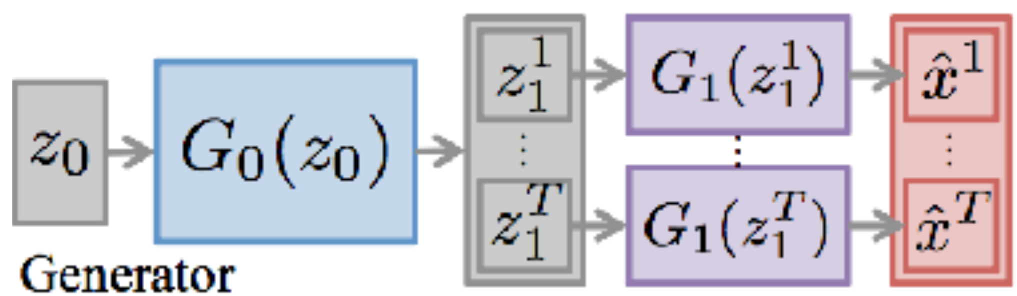
Y. Ganin, et al., ICML15]

GANs for Video

- Previous works
  - Video GAN (VGAN) [C. Vondrick, et al., NIPS16]



  - Temporal GAN (TGAN) [M. Saito, et al., ICCV17]*



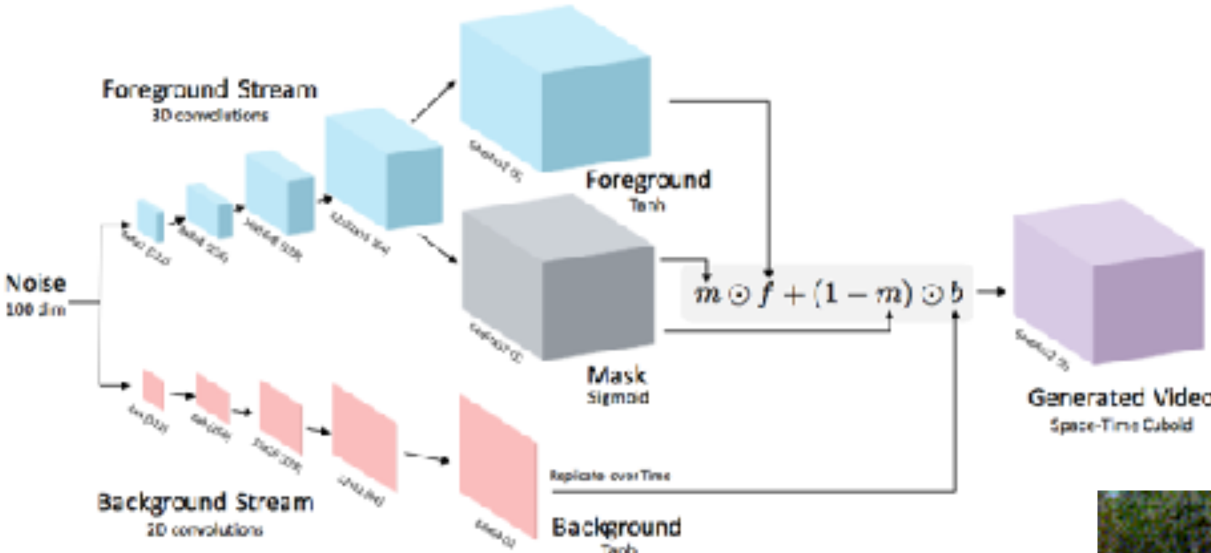
* We refer their first arXiv version in the paper because ICCV17 papers were not published yet at our submission time.

Challenges in video generation

- Important factors for realistic video generation:
  1. Realistic frame
  2. Scene consistency
  3. Reasonable motion

GANs for Video

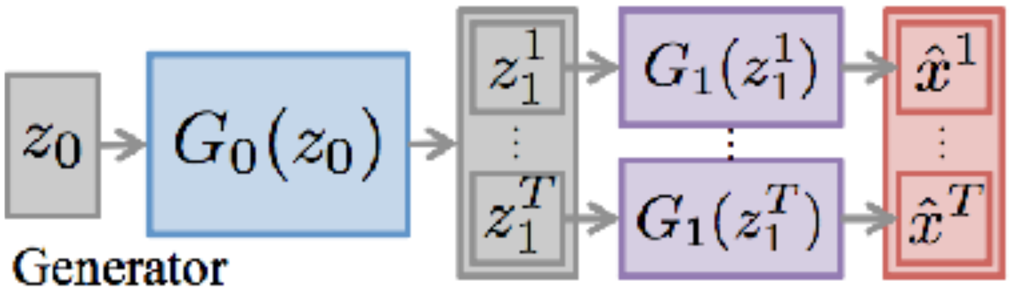
- Video GAN (VGAN) [C. Vondrick, et al., NIPS16]



1. ~~Realistic frame~~
2. Scene consistency
3. ~~Reasonable motion~~

GANs for Video

- Temporal GAN (TGAN) [M. Saito, et al., ICCV17]*



1. Realistic frame
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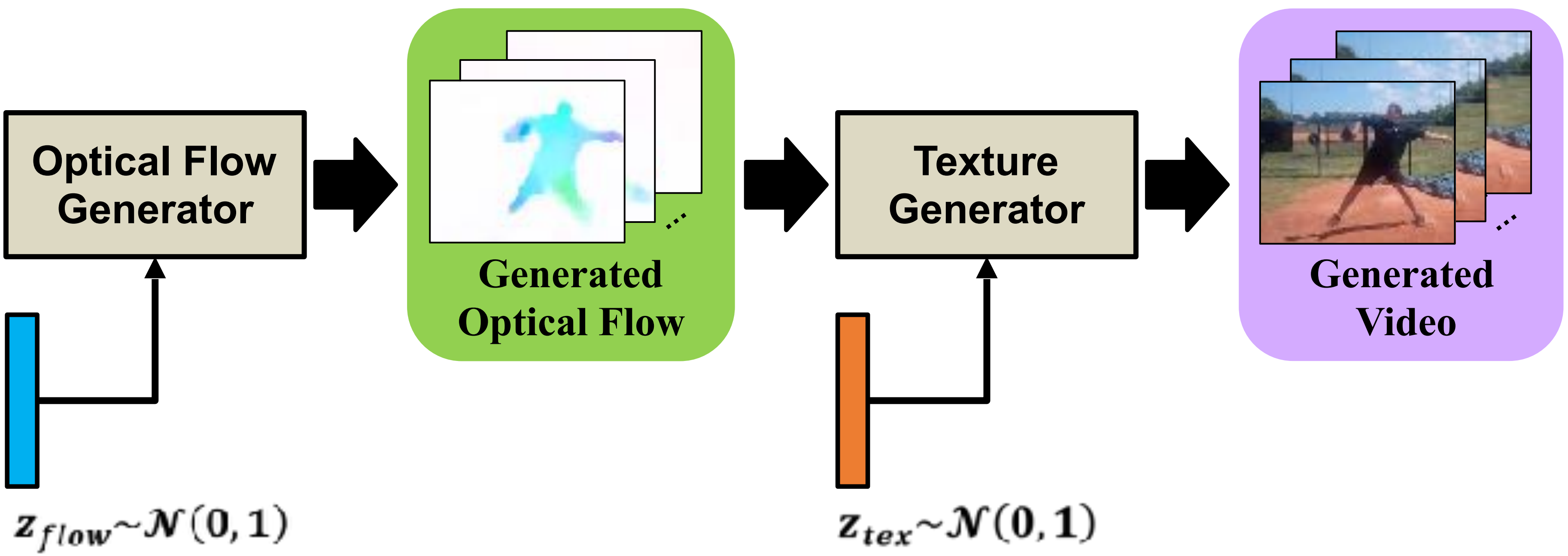
Challenges in video generation

- Important factors for realistic video generation:
  1. Realistic frame
  2. Scene consistency
  3. Reasonable motion

It is important to consider structure of video and to make a video generation pipeline that can express the structure.

Hierarchical Video Generation

- Generating video via optical flow
  1. Generate optical flow as motion information
  2. Give texture to generated optical flow



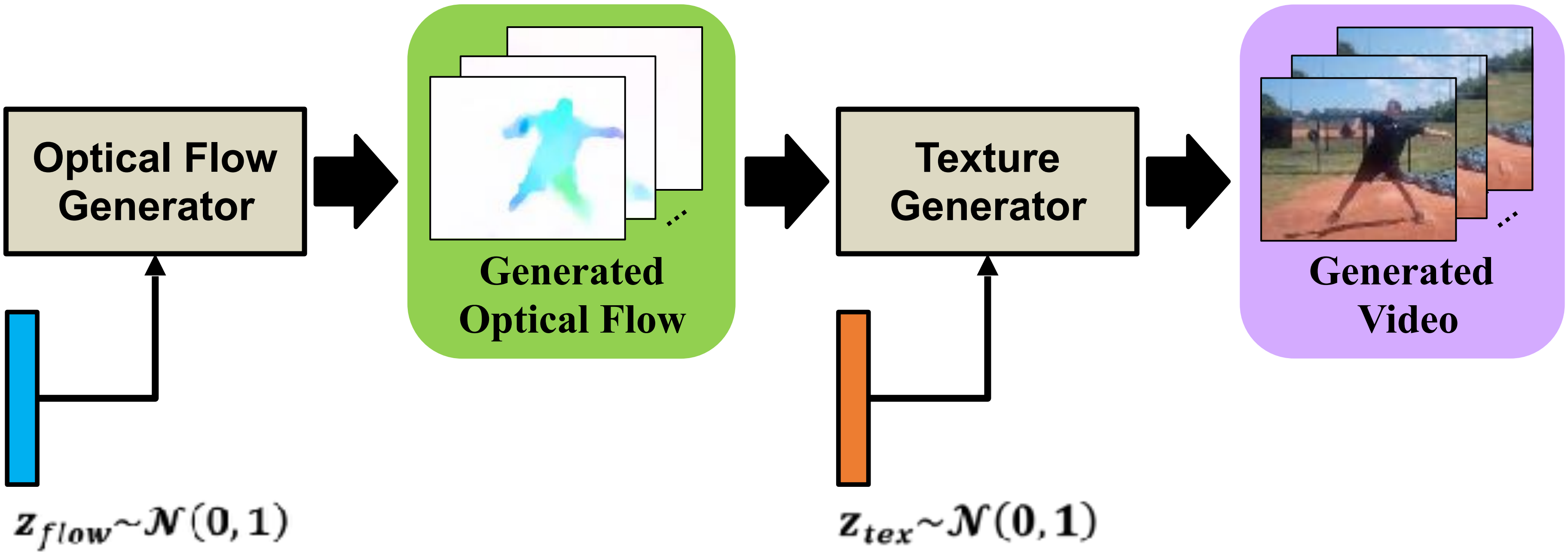
Features of Optical flow

- Extractable unsupervisedly
- Holding the contour of a moving object
- Continuity in the time direction
- No texture information

Generating optical flow first makes it …
• possible to generate a video with reasonable motion
&
• easier to generate a realistic video than without optical flow

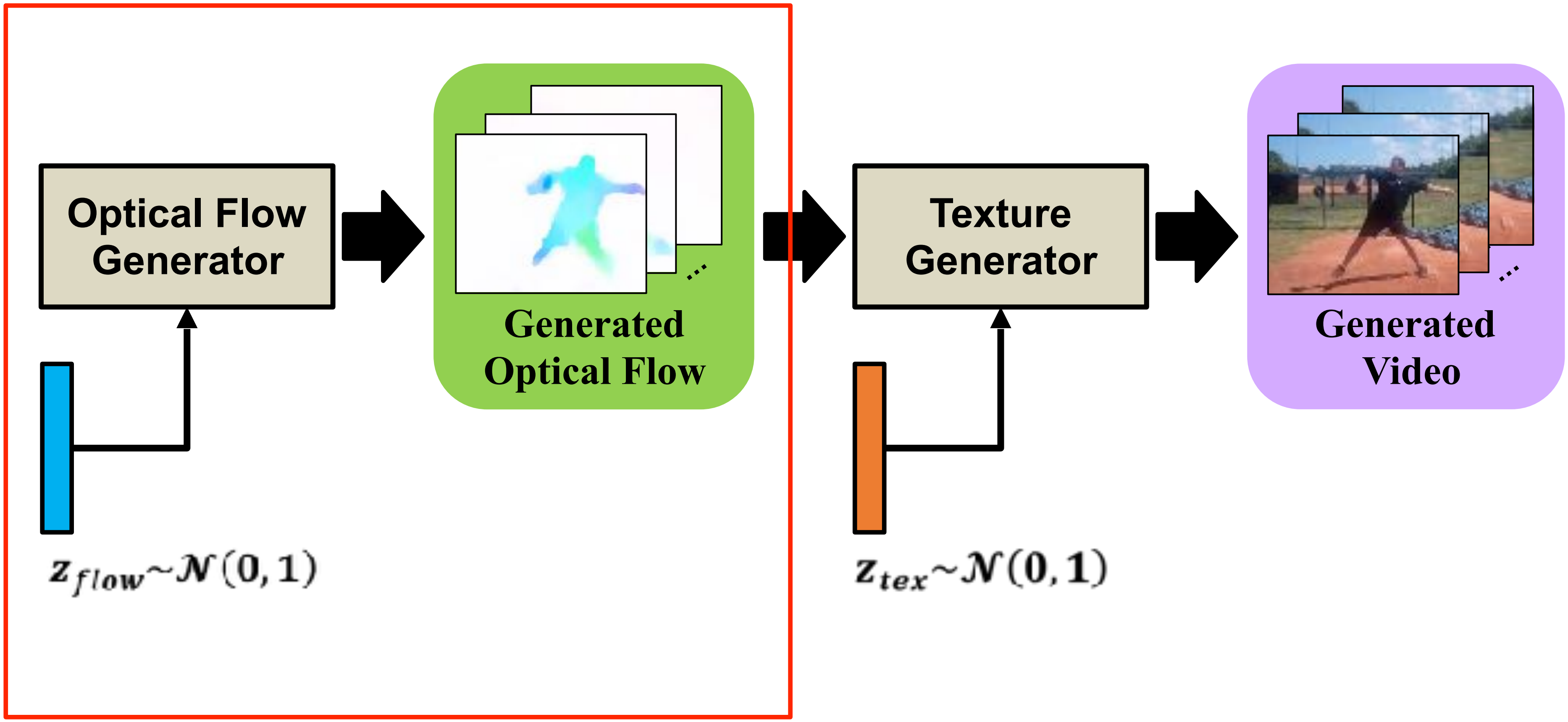
Proposed Method

- Overview of generator



Proposed Method

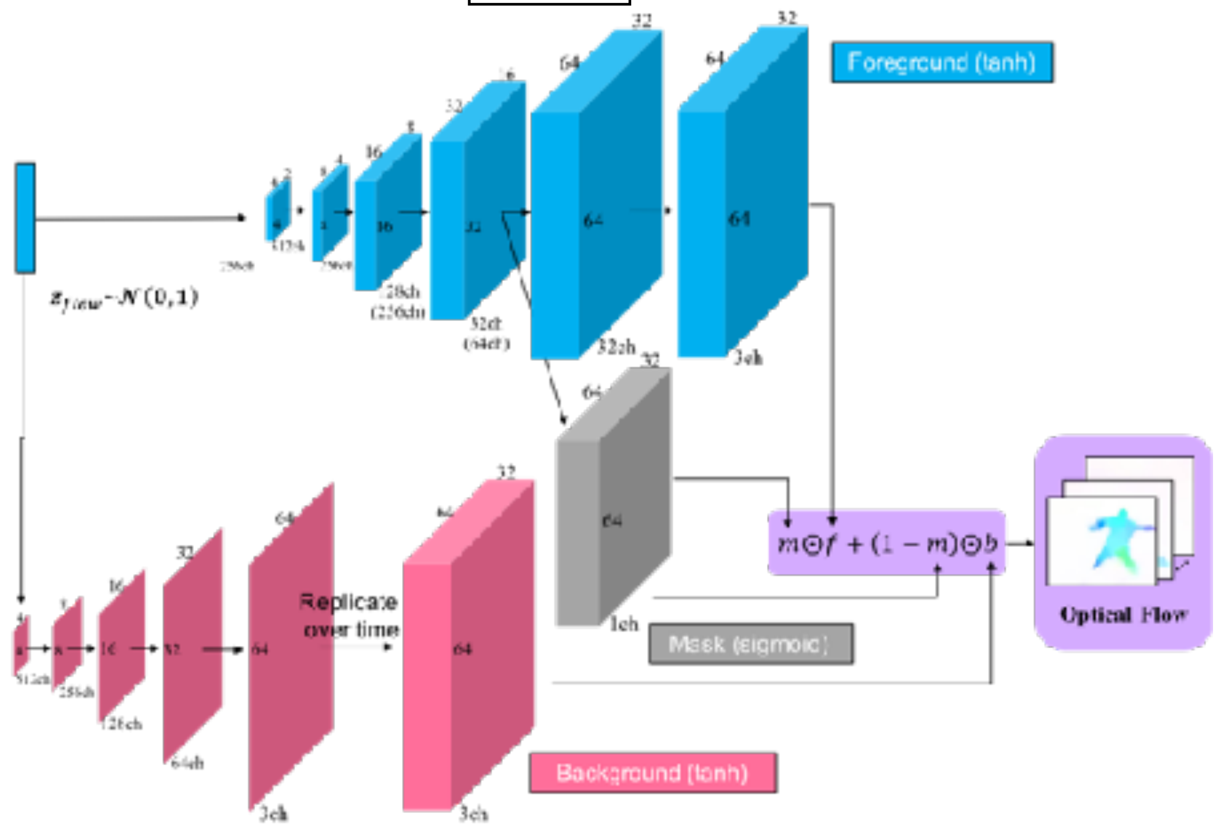
- Optical flow generator



Optical flow generator

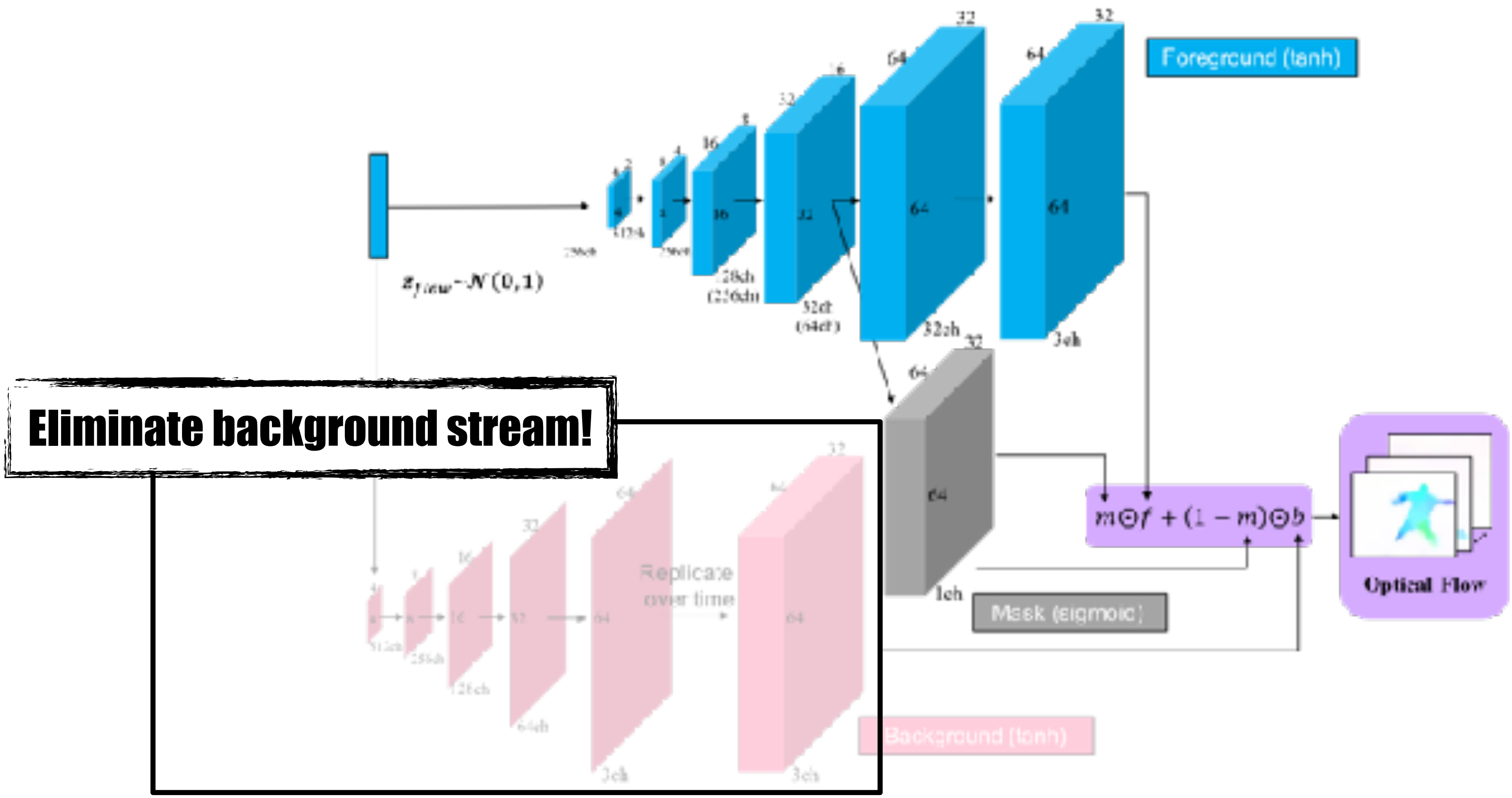
- Optical flow generator is constructed based on the pipeline of VGAN [C. Vondrick+, NIPS16].

VGAN



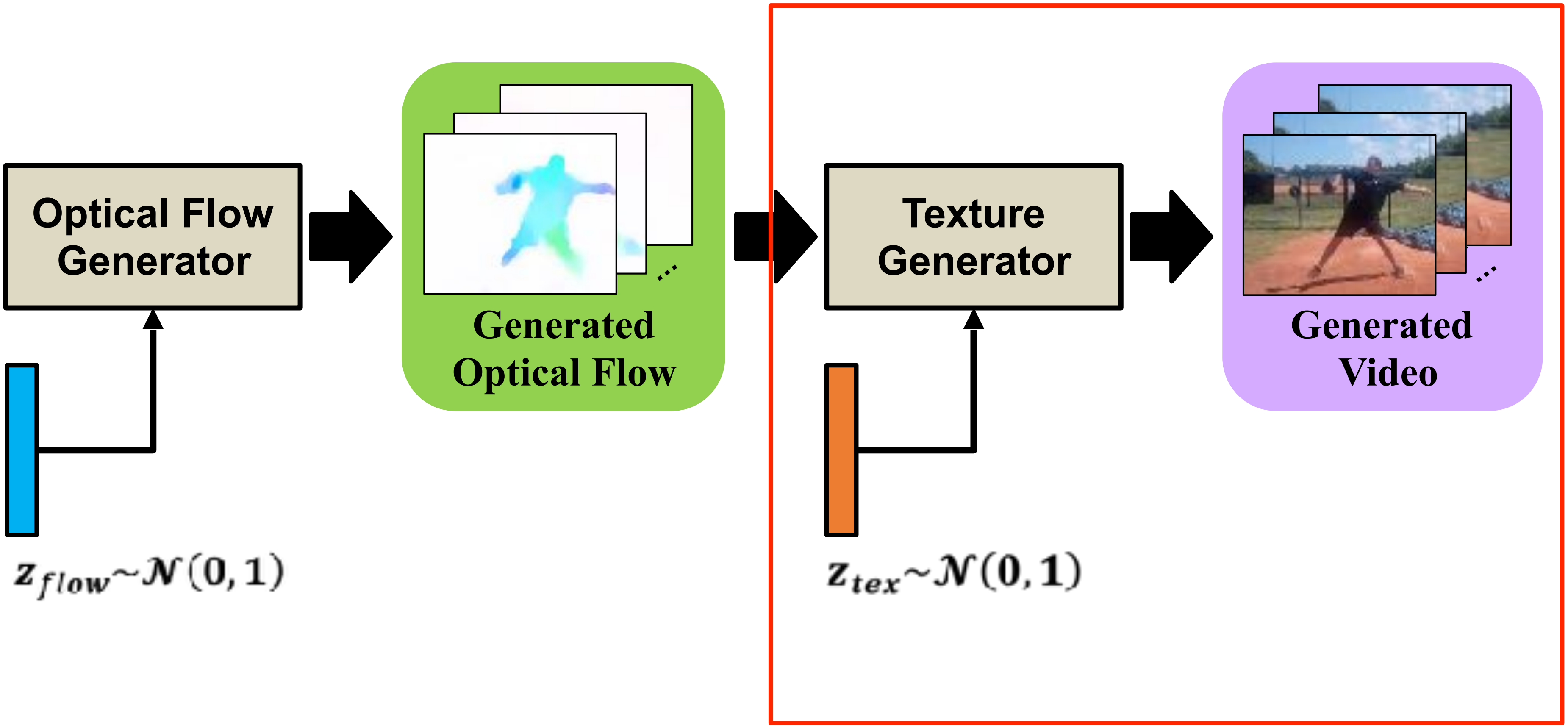
Optical flow generator

- Background optical flow should be zero
  - If the camera is fixed.



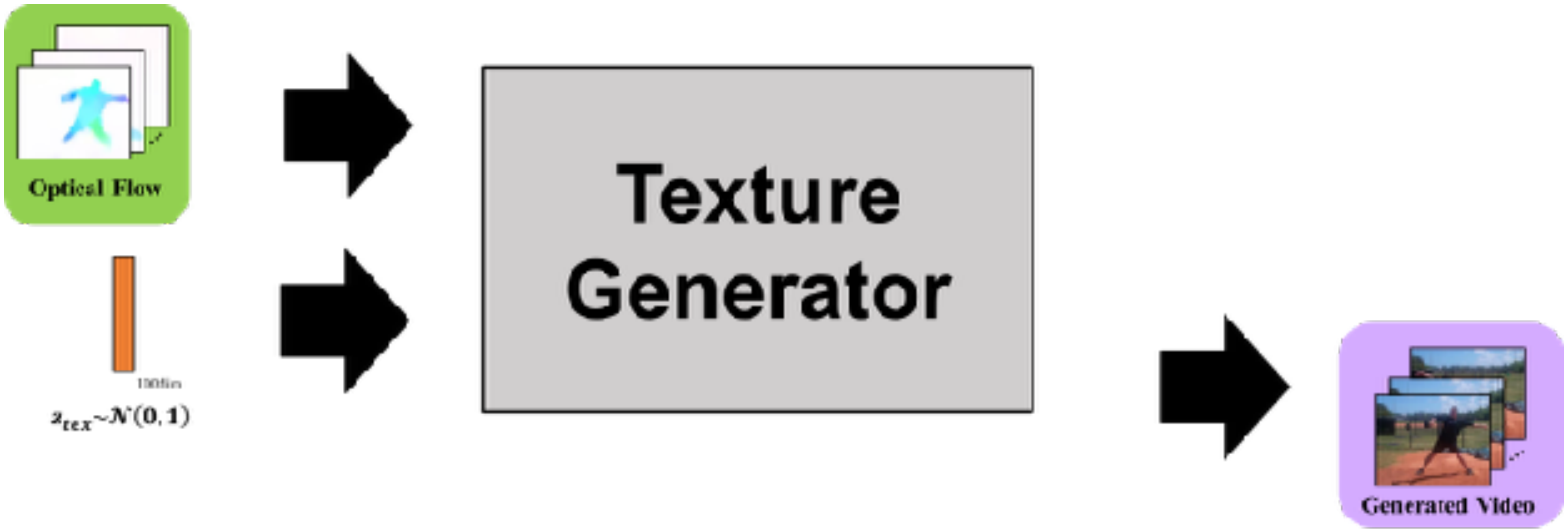
Proposed Method

- Texture generator



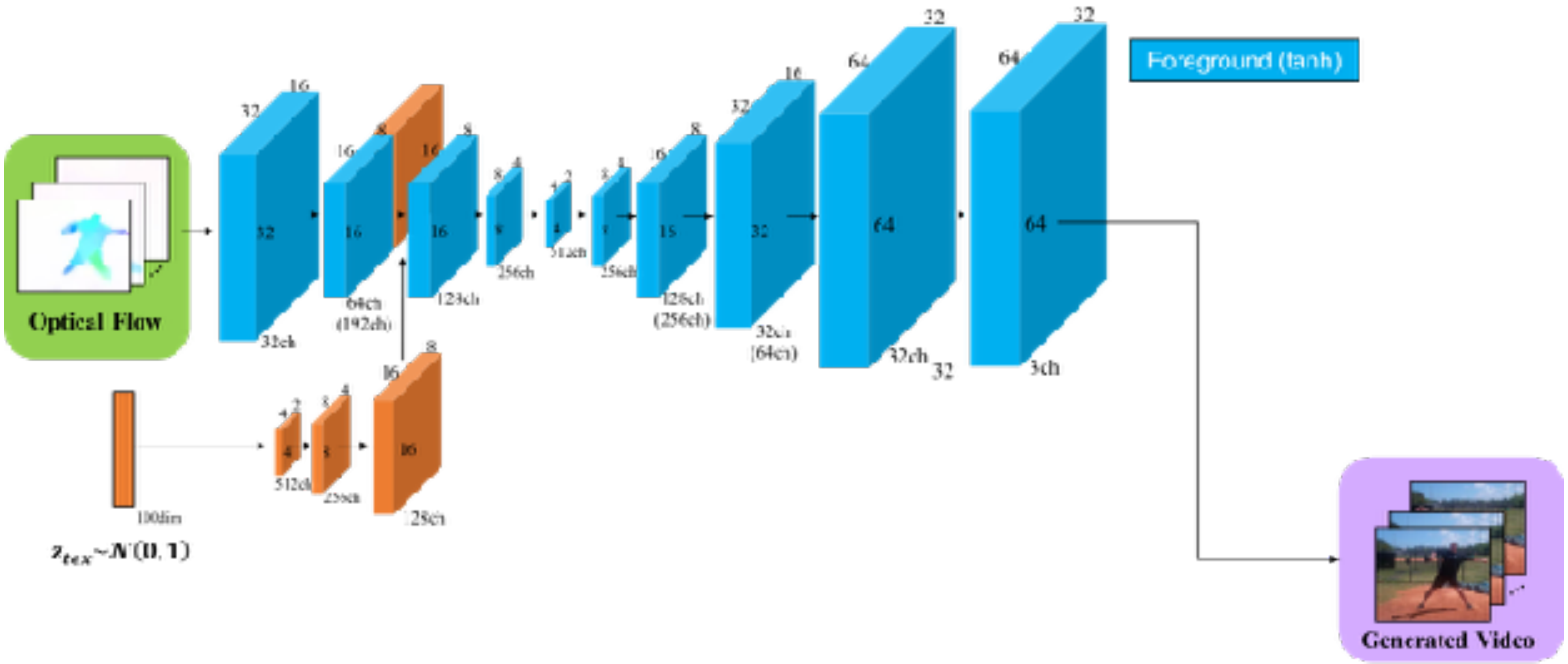
Texture generator

- Generate RGB video from random noise and optical flow.



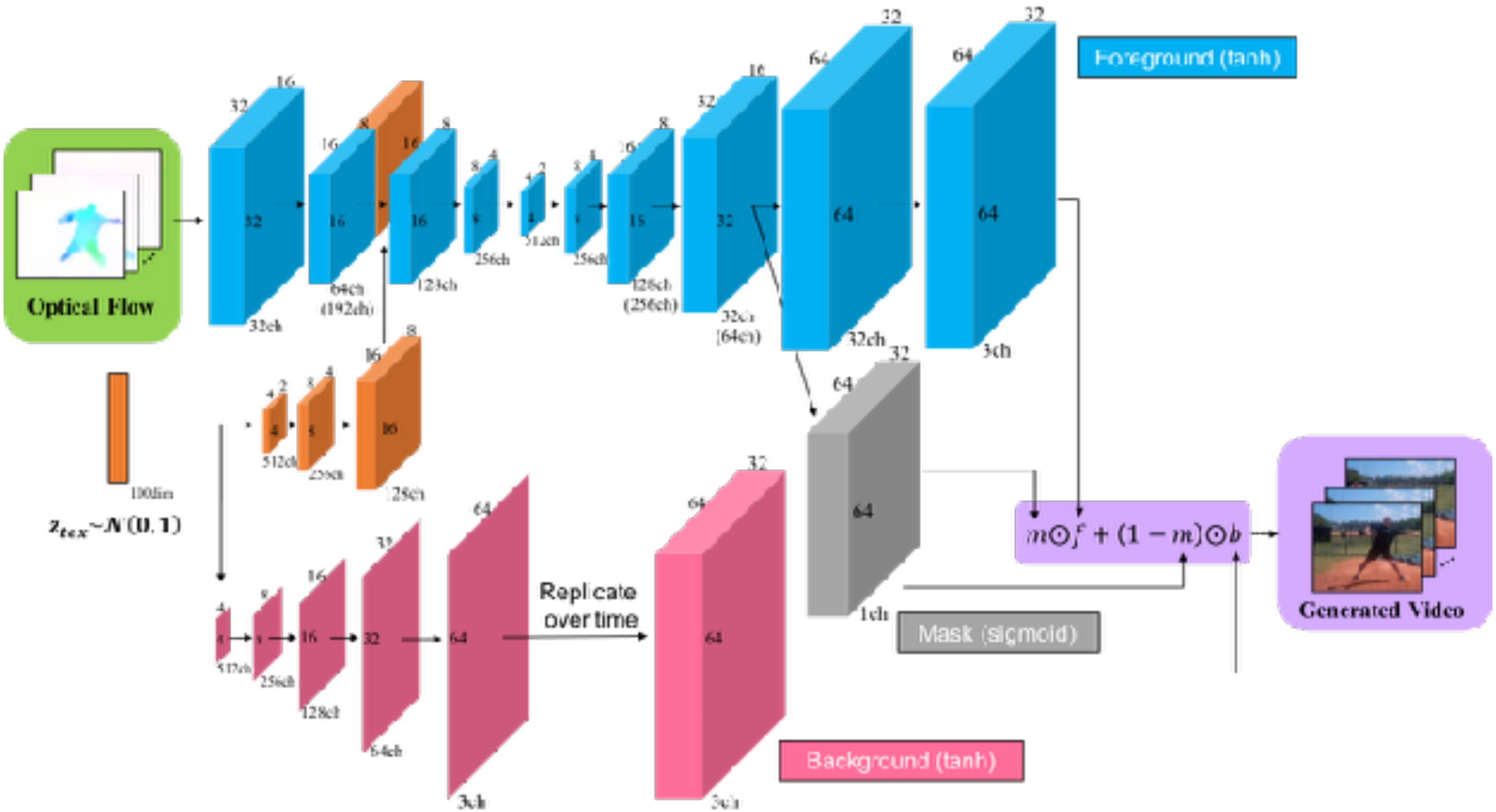
Texture Generator

- Auto-encoder that converts optical flow to RGB video



Texture Generator

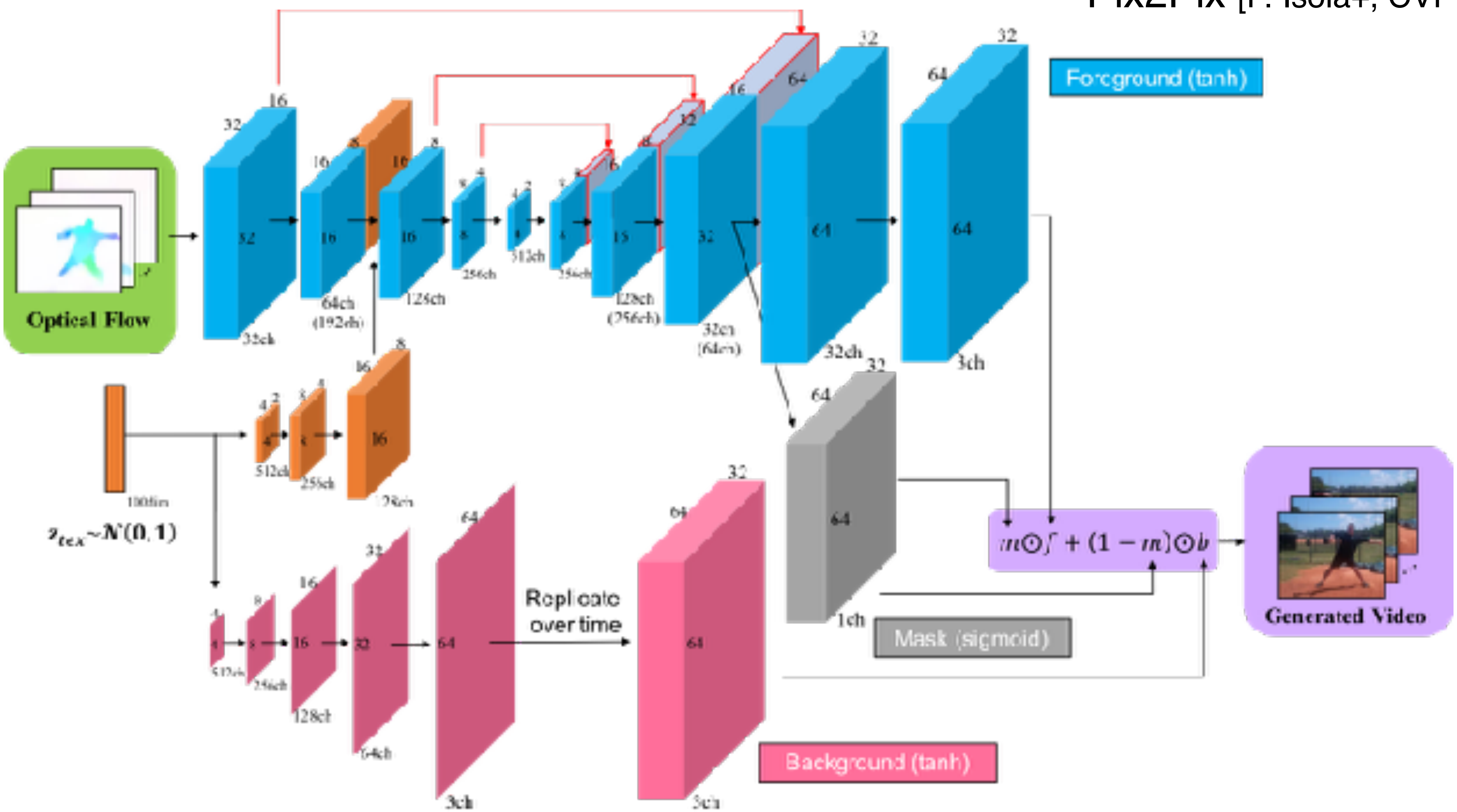
- Add background stream as VGAN
  - to obtain scene consistency



Texture Generator

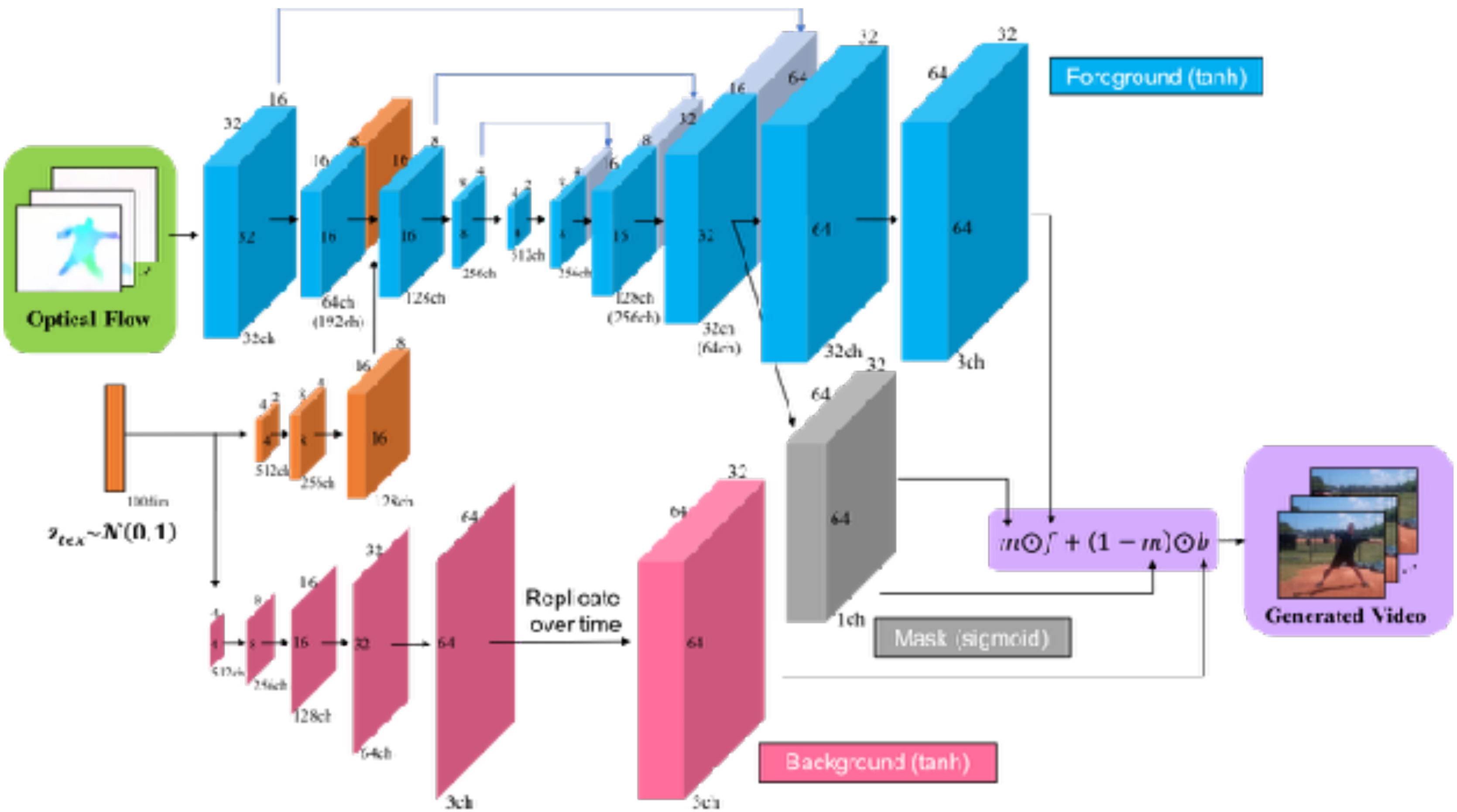
- In order to keep the contour of input, we add U-net architecture [O. Ronneberger+, MICCAI15].

cf.)
Pix2Pix [P. Isola+, CVPR17]



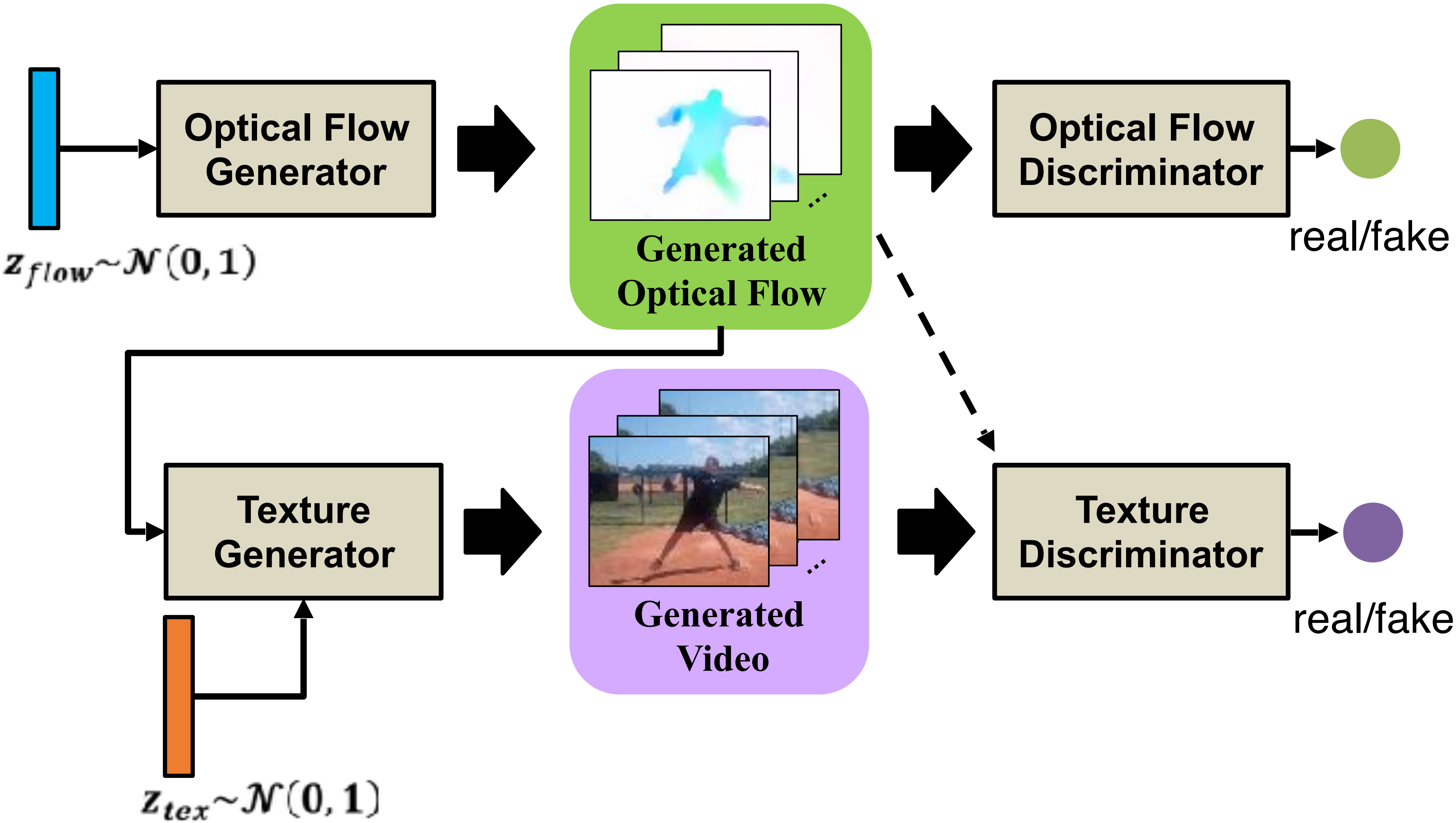
Texture Generator

- The whole pipeline of our texture generator



Overview of Proposed Method

- Hierarchical video generation via optical flow



Experiments

- Experiment 1:
  - Examples of generated results
  - Qualitative comparison with baseline
  - Human evaluation
- Experiment 2:
  - Walk in dual z
- Experiment 3:
  - Unsupervised action classification

Experiments

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Experiments

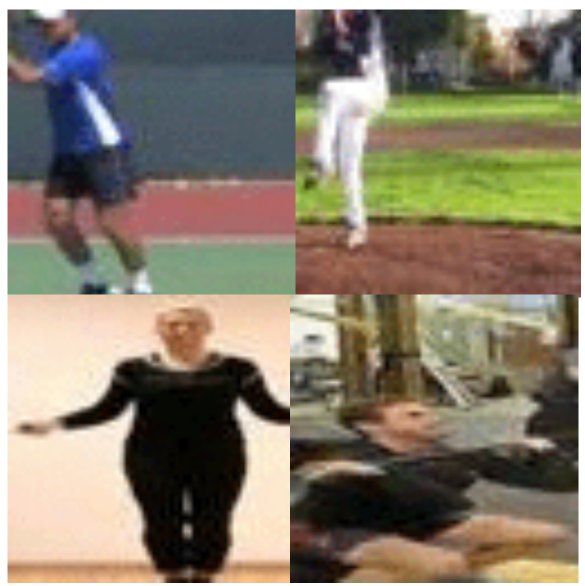
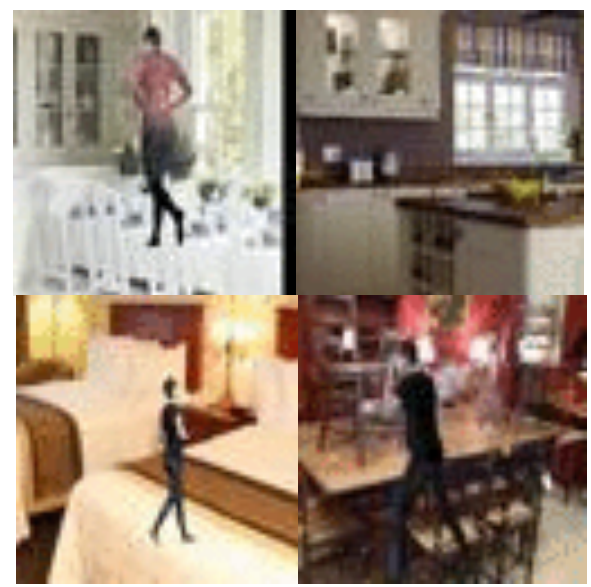
- Dataset
  - Resolution: 64x64
  - Time: 32frames (≒1~2 seconds)

Penn Action
[W. Zhang+, ICCV13]

bounding box →

Penn Action
Cropped

SURREAL
[G. Varol+, CVPR17]

Experiments

- Examples of generated results
  - Various videos

Penn Action

Penn Action Cropped

SURREAL

Experiments

Result on SURREAL

- Qualitative comparison with VGAN
  - FTGAN generates a video with reasonable motion

VGAN

FTGAN (ours)

- A person is walking without moving his legs.
- A person is walking by moving their left and right feet in turn.

Experiments

Result on PennAction cropped

- Qualitative comparison with VGAN
  - FTGAN generates a video with reasonable motion

VGAN

- The outline and the axis of rotation are unclear.

FTGAN
(ours)

- The outline and the axis of rotation are clear.

Pull-up

Experiments

- AB test on Amazon Mechanical Turk
  - Q: In which video is it easier to figure out what action is being performed?
  - 200videos
  - 9 votes on each video

Number of videos with better evaluation

	Penn Action	Penn Action Cropped	SURREAL
VGAN	76	91	95
FTGAN **(ours)**	**124**	**109**	**105**

As the complexity of the dataset increases, the proposed method becomes effective

Experiments

- Experiment 1:
  - Examples of generated results
  - Qualitative comparison with baseline
  - Human evaluation
- Experiment 2:
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- Experiment 3:
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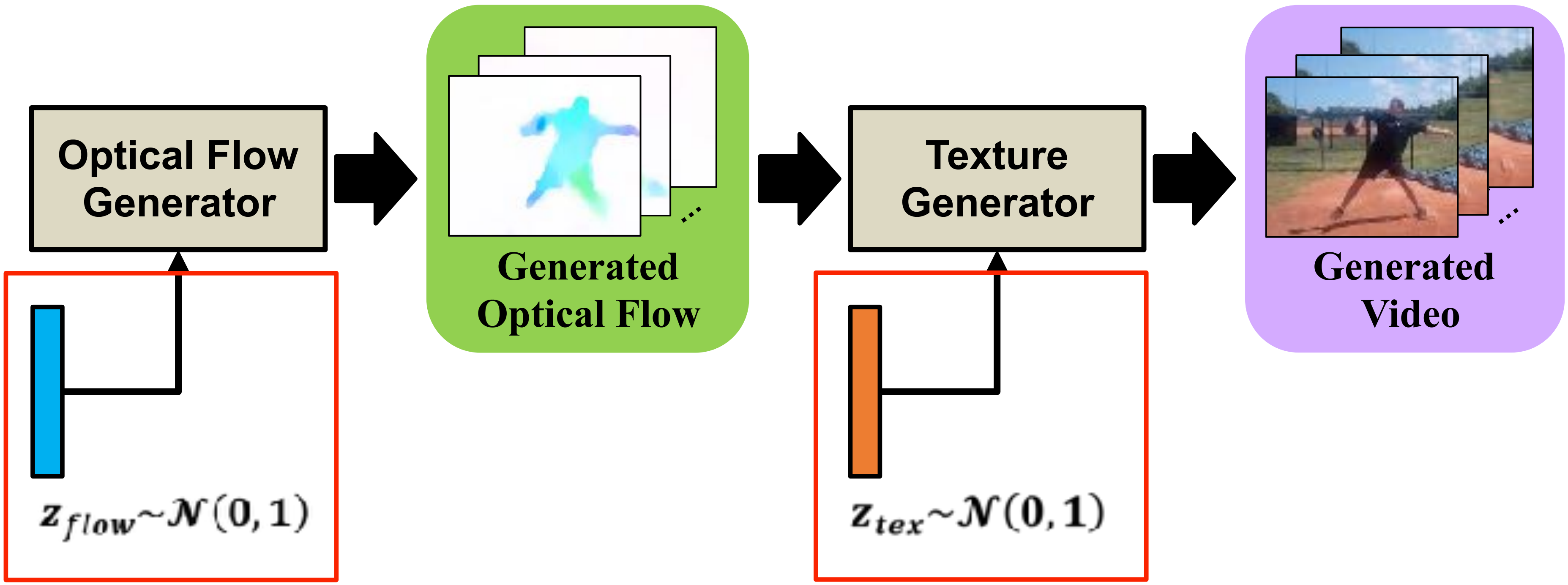
Experiments

- Overview of generator

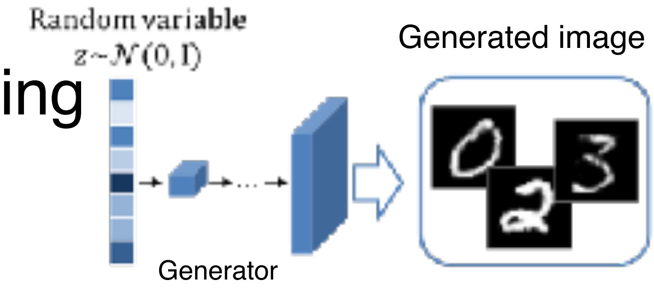


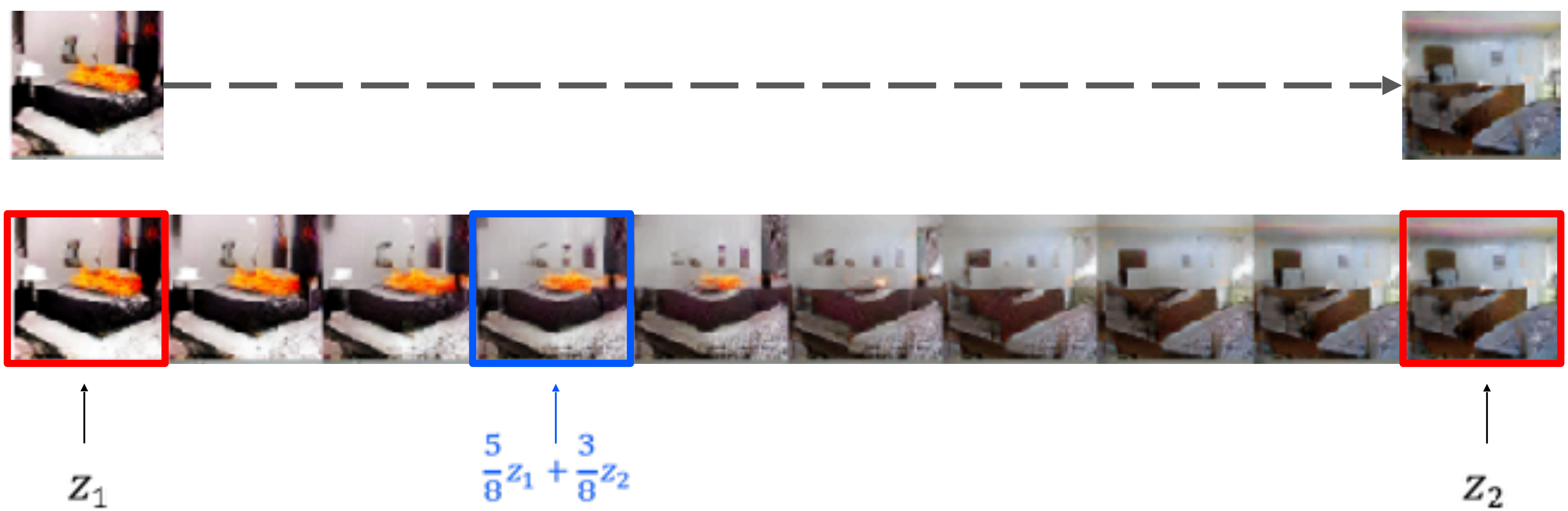
z_flow generates **motion**

z_tex generates **appearance**

Experiments

- Walk in z
  - Conforming mode-collapse avoiding
  - Mixing two images at any ratio





[A. Radford+, ICLR16]

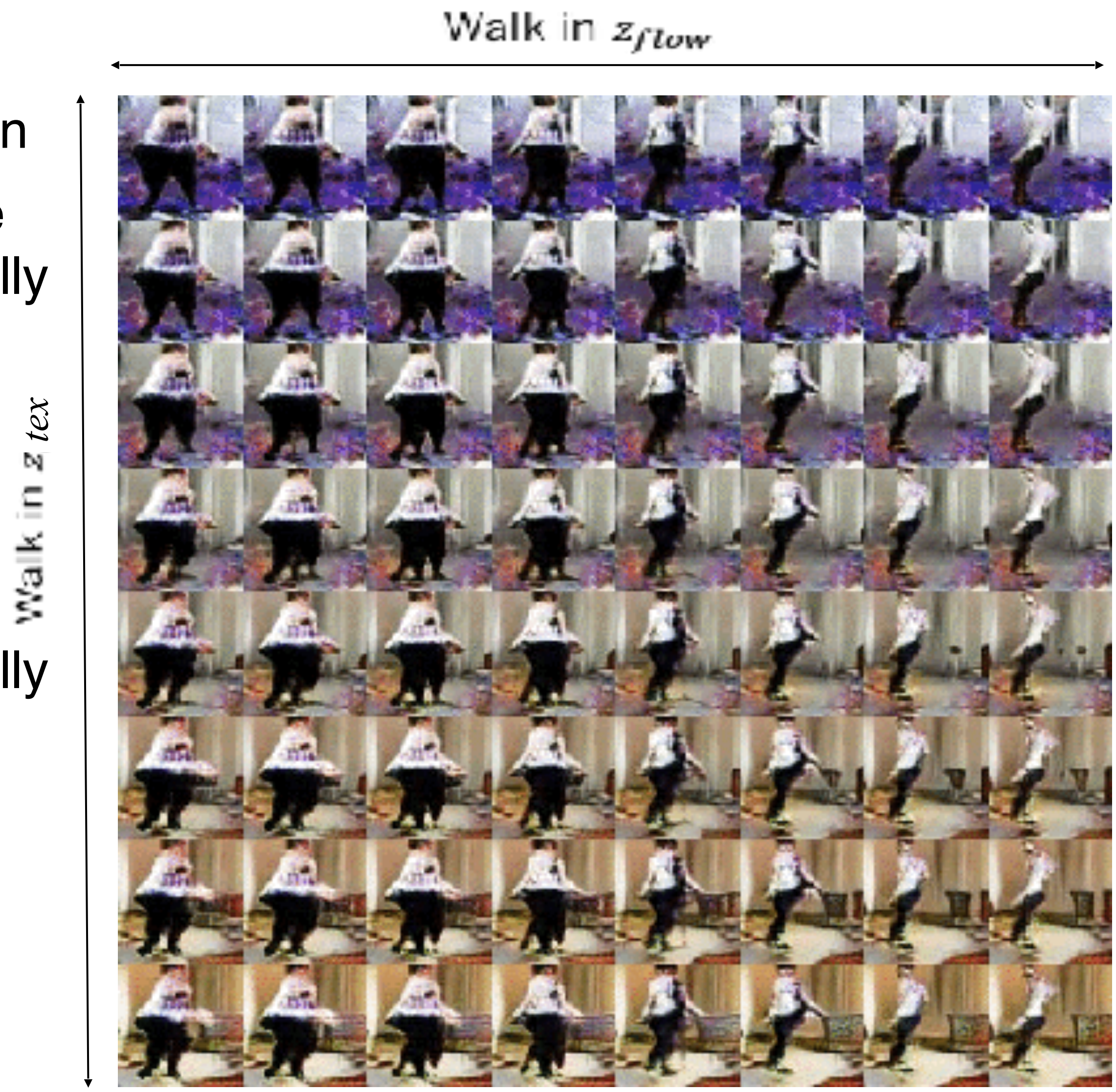
Experiments

- Dataset
  - SURREAL [G. Varol+, CVPR17] cropped

Crop videos with bounding box

Experiments

- Walk in z_flow
  - The same motion
  - The appearance changes gradually
- Walk in z_tex
  - The same appearance
  - The motion changes gradually



Experiments

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- Walk in z_tex
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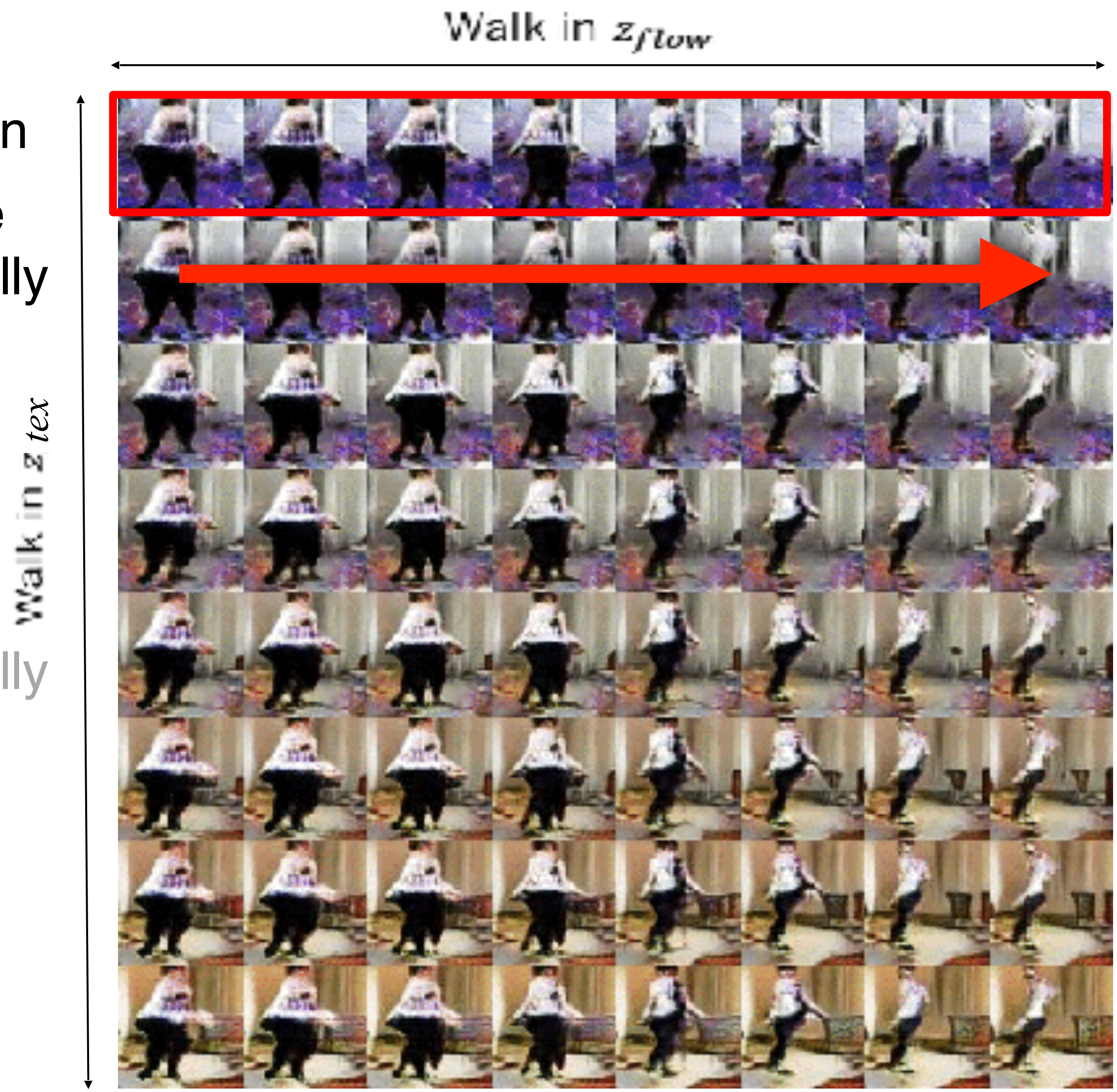

Experiments

- Walk in z_flow
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  - The appearance changes gradually
- Walk in z_tex
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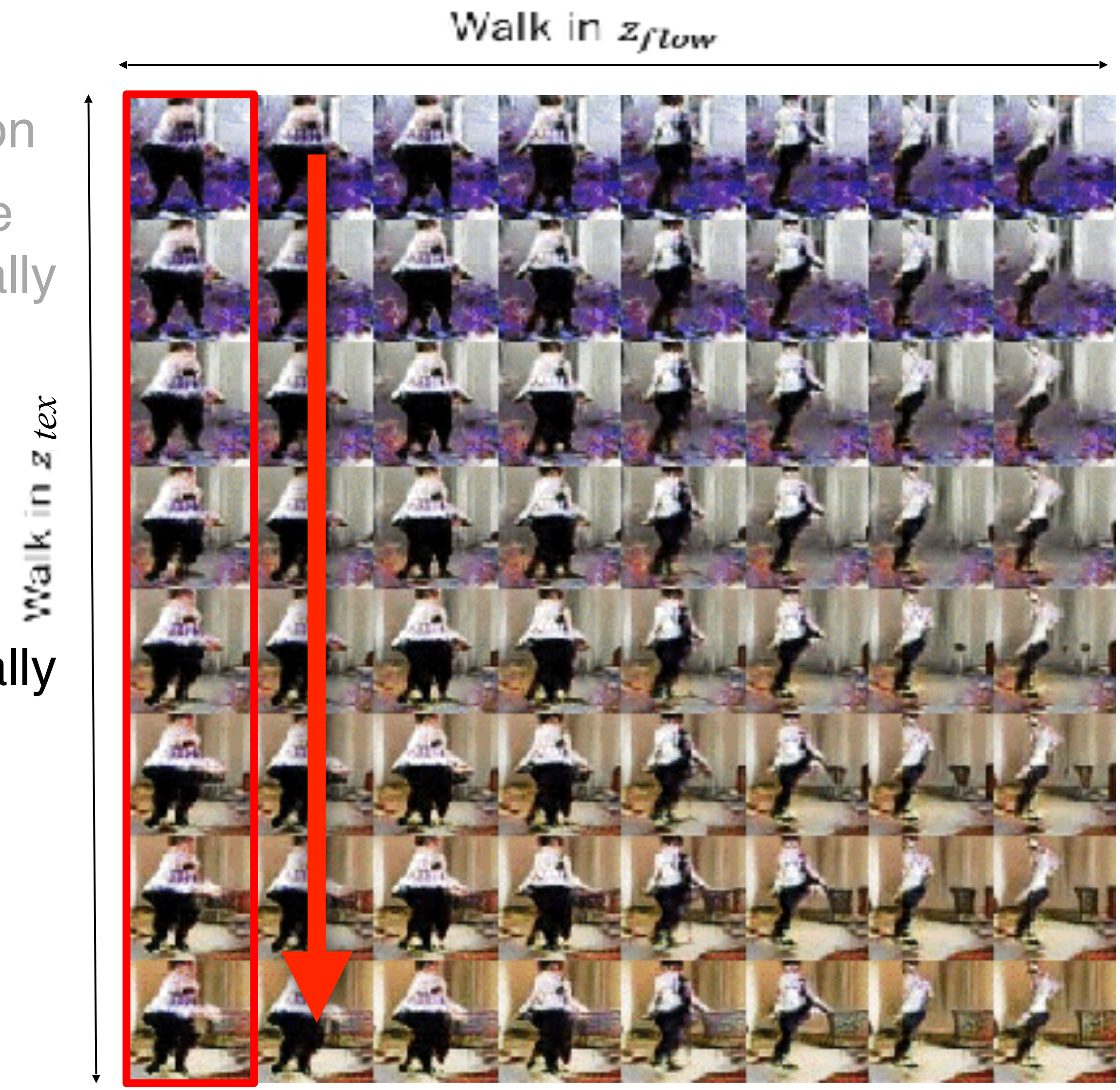
  - The motion changes gradually



Experiments

- Walk in z_flow
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  - The appearance changes gradually
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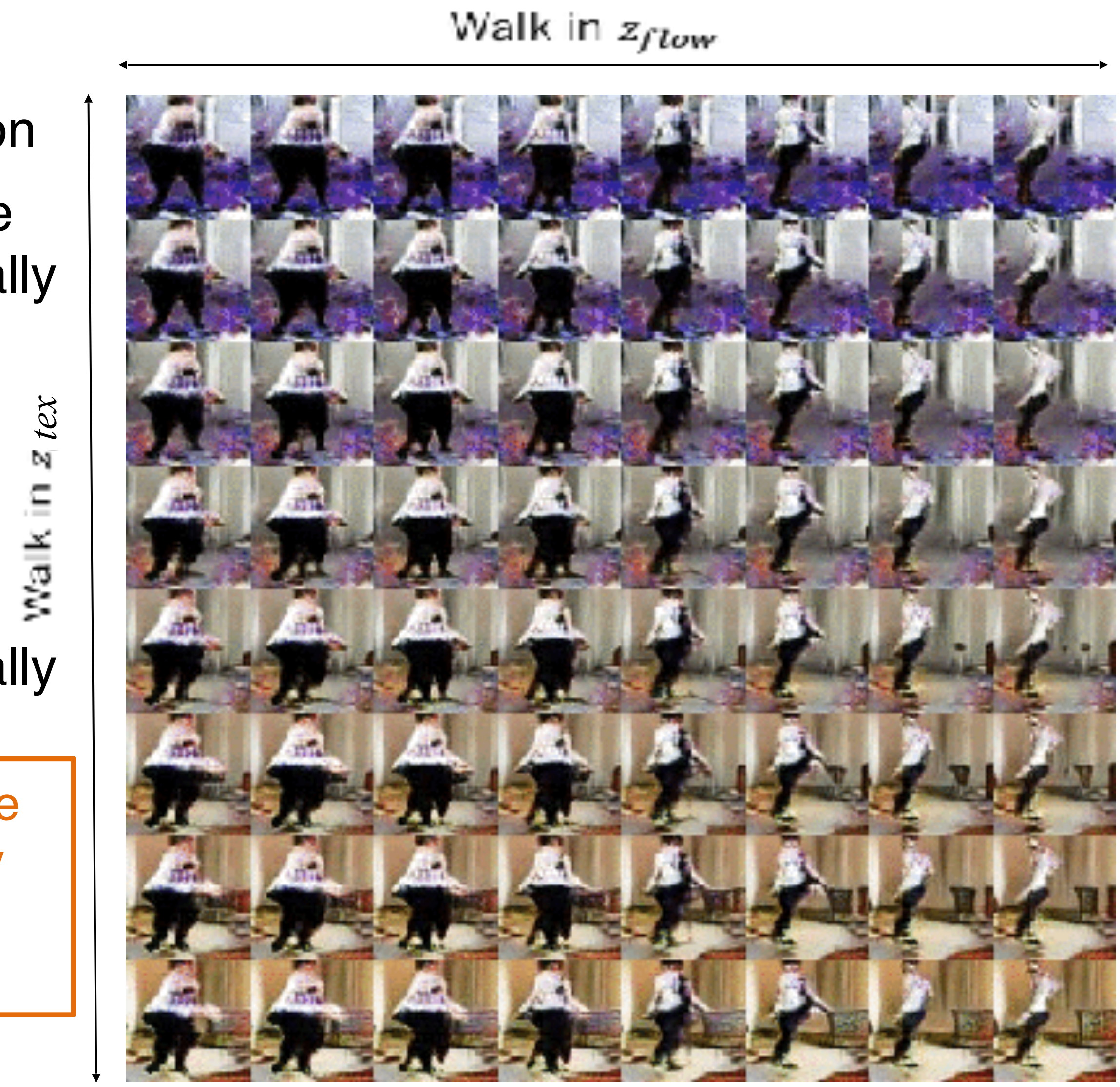

Our method can generate videos by independently controlling motion and appearance

Experiments

- Experiment 1:
  - Examples of generated results
  - Qualitative comparison with baseline
  - Human evaluation
- Experiment 2:
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- Experiment 3:
  - Unsupervised action classification

Experiments

Purpose

- Investigate the unsupervised feature expression learning capability as the same way with previous works

Method

- Extract the last layer in discriminator as feature

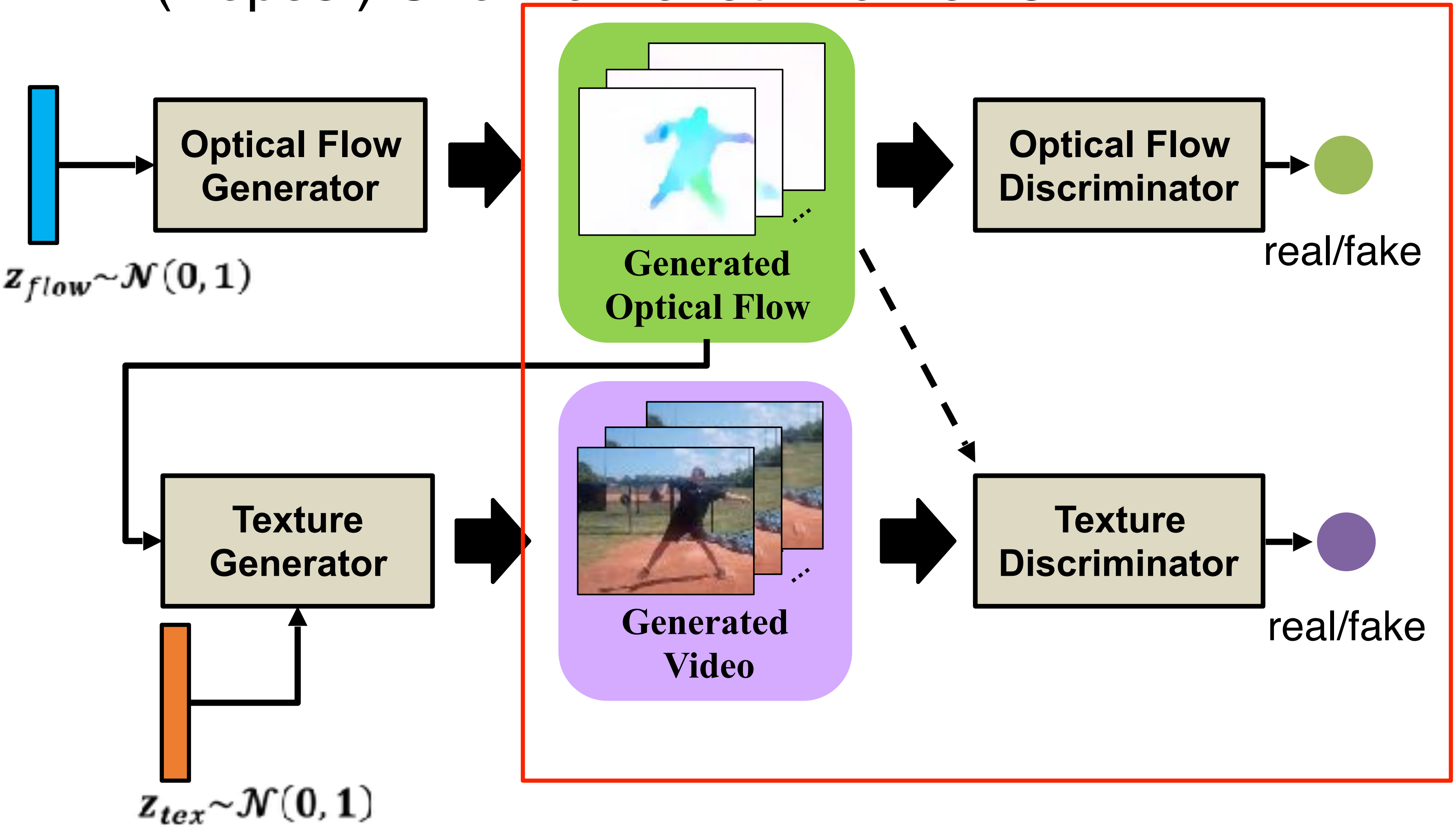
Setting

- Dataset: UCF101 [K. Soomro, et al., arXiv 2012]
  - 101 classes
  - 13320 videos
- Classifier: SVM

All of these settings are following previous works (VGAN and TGAN).

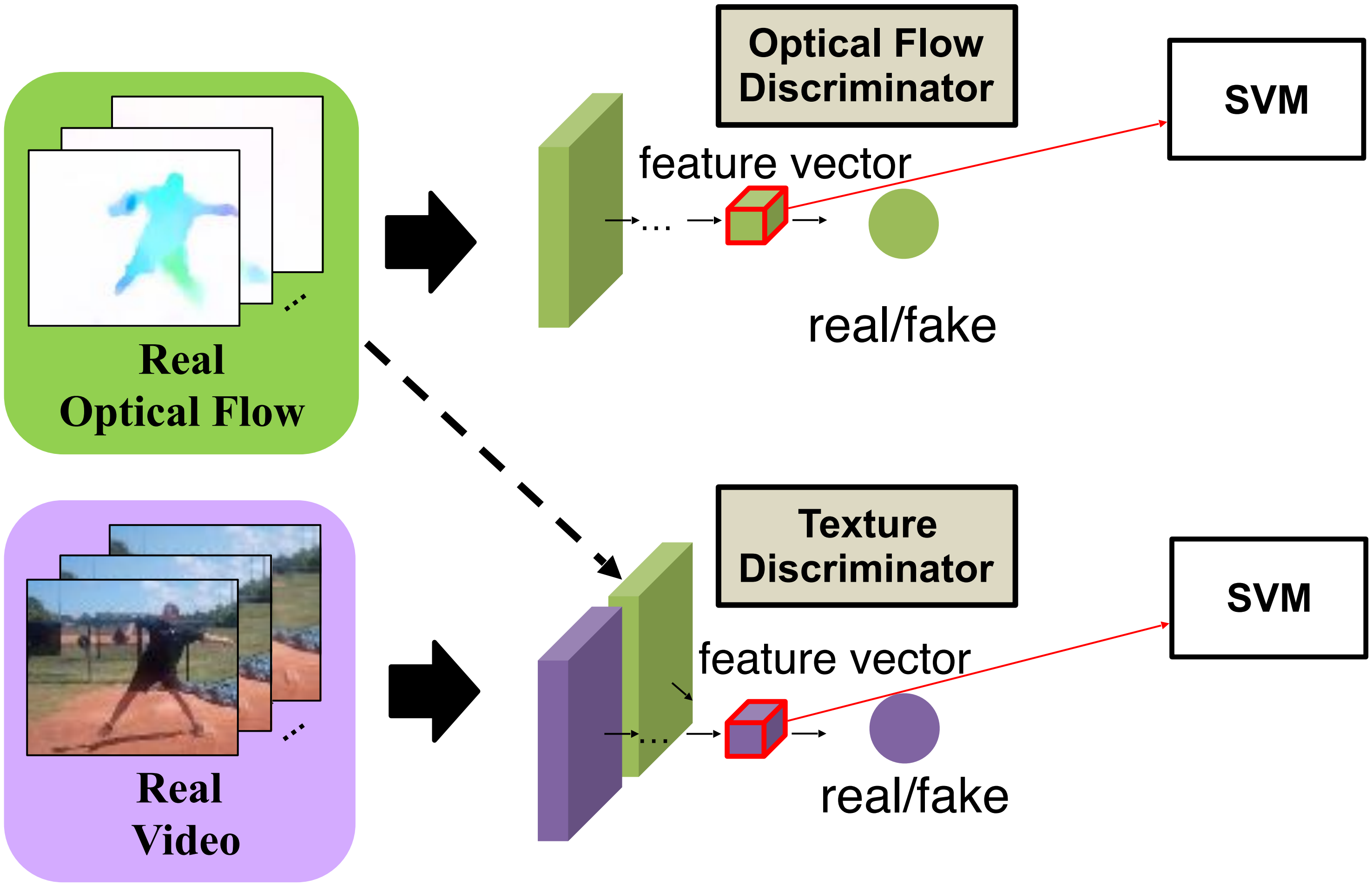
Experiments

- (Repost) Overview of our networks.



Experiments

- Extract the last layer of discriminator as feature vector



Experiments

- Late fusion of flow-discriminator and texture-discriminator improves recognition accuracy.
  - Features learned by each network is complementary, which means…
    - Flow-discriminator learns **motion** information
    - Texture-discriminator learns **appearance** information

Method	**Accuracy**
Chance	0.9%
(a) Flow-discriminator + Linear SVM **(ours)**	**48.0%**
(b) Texture-discriminator + Linear SVM **(ours)**	**50.3%**
(a) + (b) FTGAN (fusion by Linear SVM) **(ours)**	**59.7%**

+

Experiments

- FTGAN outperforms VGAN and TGAN
  - Separating information ensures the capture of much richer video characteristics

Method	**Accuracy**
Chance	0.9%
VGAN + Random Init [C. Vondrick+, NIPS16]	36.7%
TGAN: Image-discriminator + Linear SVM [M. Saito et al, arXiv]	38.6%
TGAN: Temporal-discriminator + Linear SVM [M. Saito et al, arXiv]	23.3%
(a) Flow-discriminator + Linear SVM **(ours)**	**48.0%**
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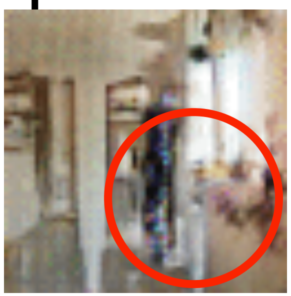
outperform!

Summary

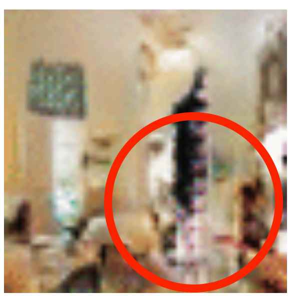
Thank you!

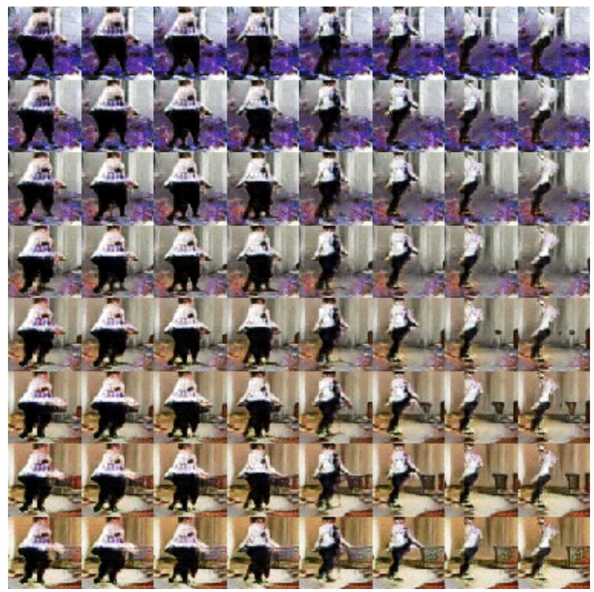
- We propose a hierarchical video generative model via optical flow: FTGAN.
- Experiments:

VGAN



FTGAN





UCF101

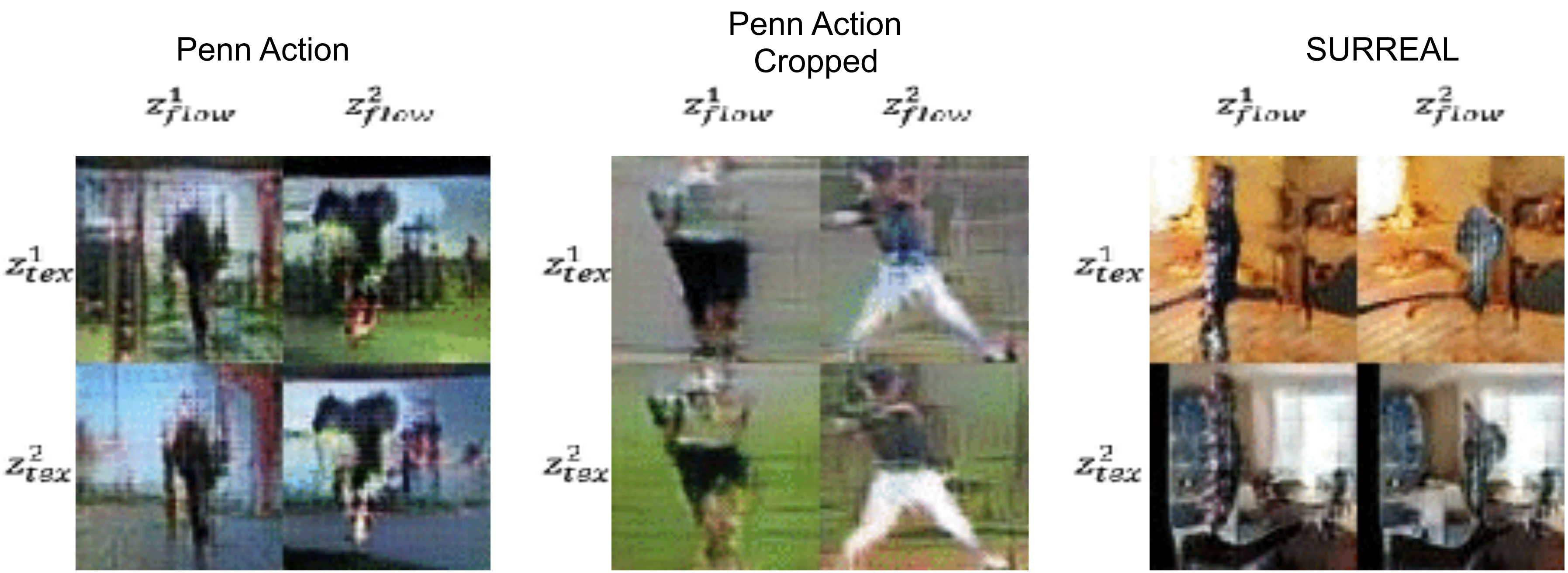
Method	Accuracy
VGAN	36.7%
TGAN	38.6%
FTGAN	**59.7%**

It is important to consider structure of video and to make a video generation pipeline that can express the structure.

- Fin
- 終

Experiments

- Does z_flow generates motion and z_tex generates appearance independently?
  - vertical: generated from the same z_flow
  - Horizontal: generated from the same z_tex



Experiments

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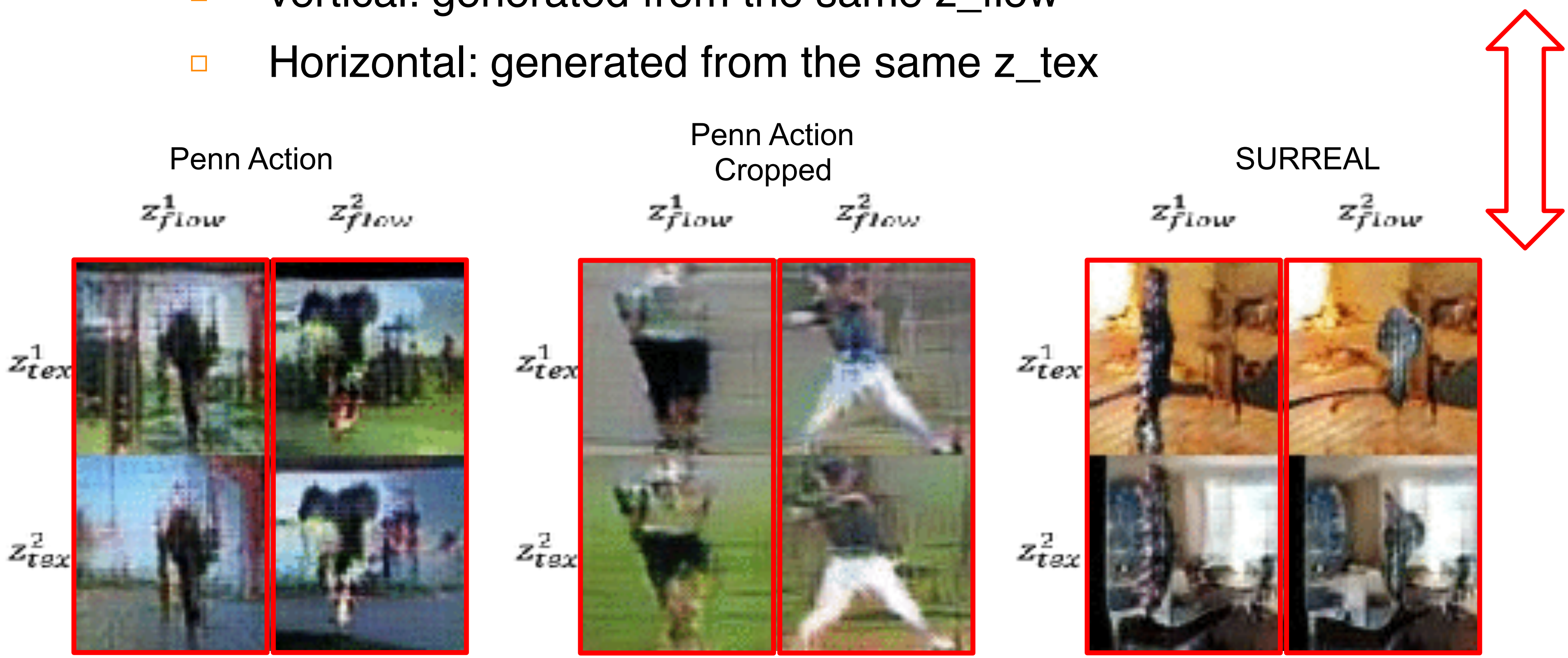
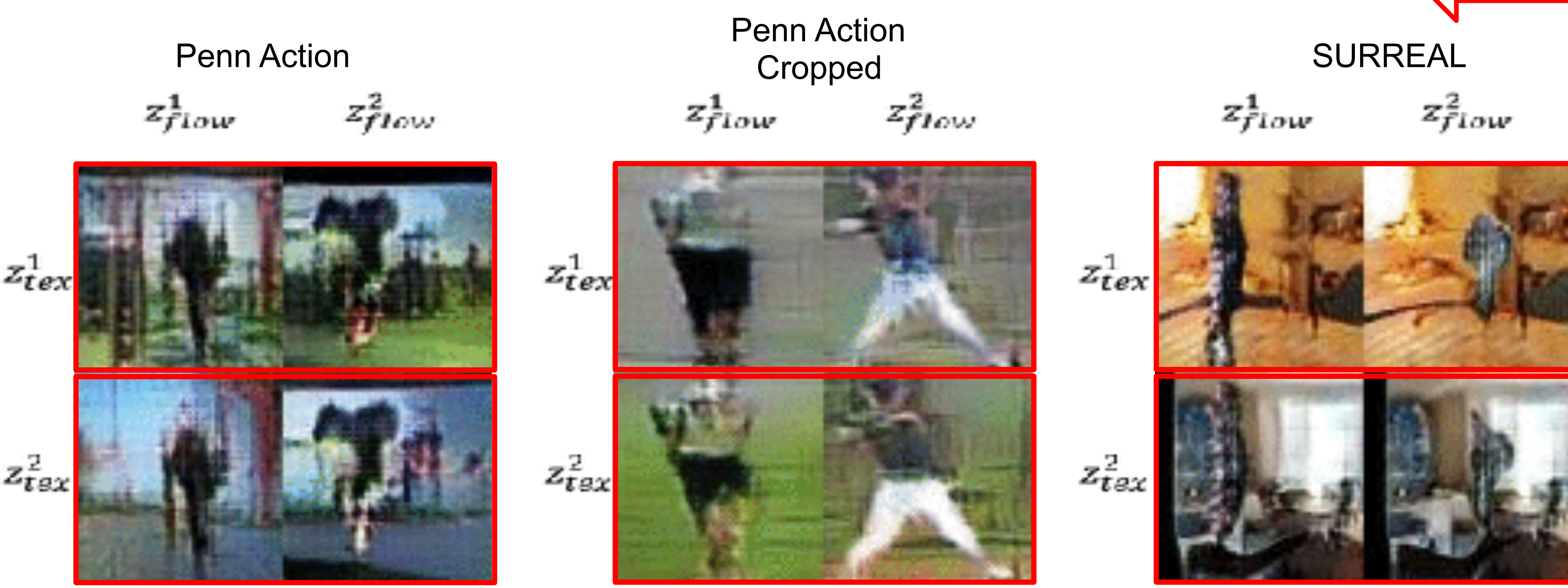


The same movements and different appearance

Experiments

- Does z_flow generates motion and z_tex generates appearance independently?
  - vertical: generated from the same z_flow
  - Horizontal: generated from the same z_tex



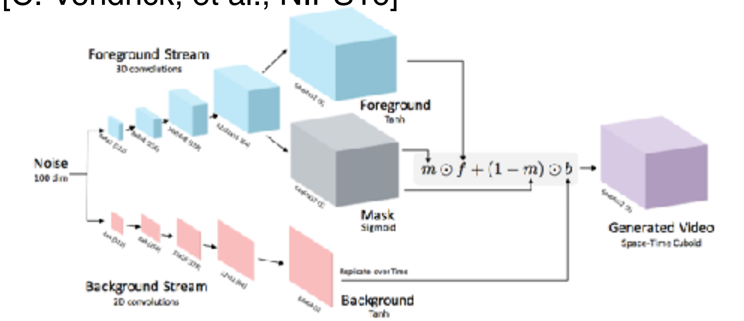
Different movements and the same appearance

動画生成の難しさ

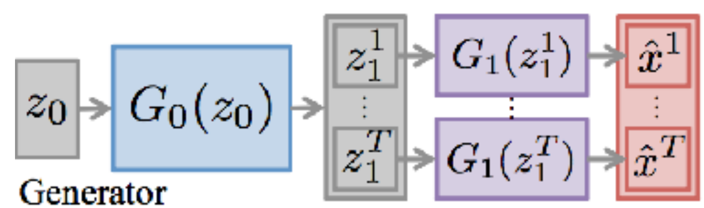
- 生成された動画が本物らしくあるためには, 以下の3つの条件を満たしている必要がある
  a. 各フレームがきれいな画像になっている
  b. 動画内でのシーンの一貫性が保たれている
  c. 動きが妥当なものになっている

\- GANを動画生成に拡張した手法

Video GAN (VGAN)
[C. Vondrick, et al., NIPS16]



Temporal GAN (TGAN)
[M. Saito et al, arxiv]



関連研究 -動画生成-

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手法: VGAN [C. Vondrick, et al., NIPS16]

- 動くものを前景、動かないものを背景として生成
  - 動画内で同じシーンが現れる
- 3D convolutionを使用
  - 見た目と動きを同時に学習

生成結果

関連研究 -動画生成-

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手法: TGAN [M. Saito et al, arxiv]

- 2D convolutionをXY方向にかけた後、1D convolutionをT方向に
  - 動き情報が見た目情報を抽象化された状態でしか取れてい

生成結果

実験

- 生成結果: TextureGAN (Optical flowを与えた場合)

Penn Action			SURREAL		
GT optical flow	Generated video	GT video	GT optical flow	Generated video	GT video

実験

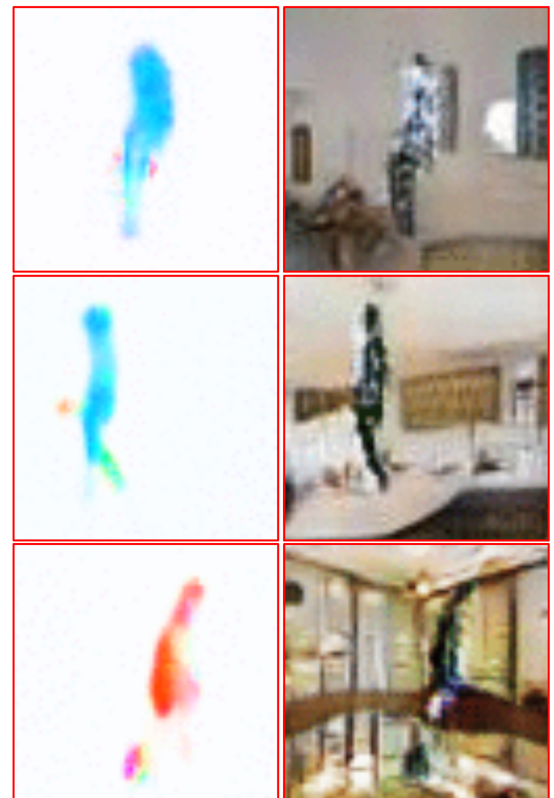
- 生成結果: FTGAN (Optical flowも生成)

Penn Action

Generated optical flow | Generated video

SURREAL

Generated optical flow | Generated video



実験

未完成

- VGANとの比較
  - Penn Action

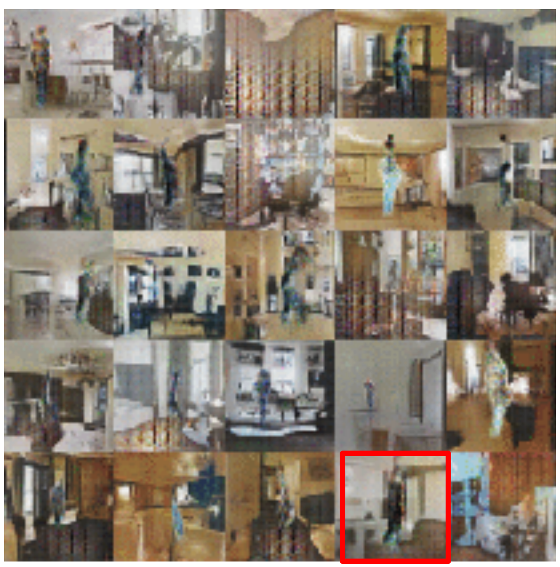
VGAN　TextureGAN　FTGAN

未完成

実験

- VGANとの比較
  - SURREAL

VGAN



TextureGAN

FTGAN