Deformation Models for Image and Video Generation

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Institut polytechnique de Paris, France

Multimedia and Human Understanding Group (MHUG),
University of Trento, Italy

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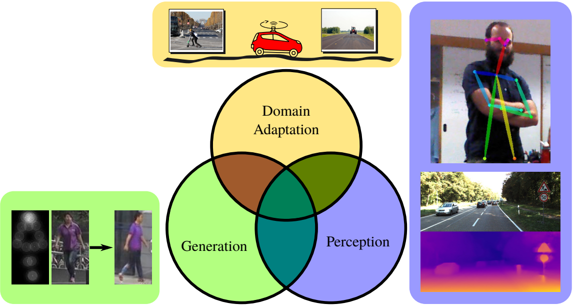
Who am I?



PhD — Post-Doc — Assistant Professor

2014 — **Perception** Dr. R. Horaud

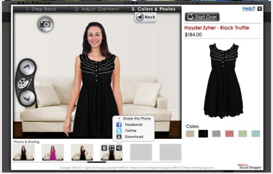
2018 — **MHUG** Prof. Nicu Sebe

2019 — **Multimedia** Prof. Marco Cagnazzo

Artistic / Editing / marketing purposes

- Photo editing

- Augmented reality [a]

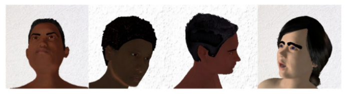


- Many other applications: video games, increasing some intrinsic image properties...

[a] image from *zugara* company

Machine Learning Tasks

- Generate annotated data: Head pose [1]

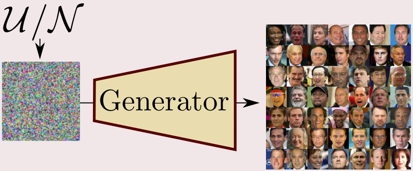


- Learning from few samples
- Domain adaptation

[1] **S.Lathuilère**, R.Juge, P.Mesejo, R.Munoz-Salinas, R.Horaud, Deep Mixture of Linear Inverse Regressions Applied to Head-Pose estimation, CVPR 2017

Image Generation

From Noise to Image



[4] P.Isola, J.-Y.Zhu, T.Zhou, A.A.Efros, Image-to-Image Translation with Conditional Adversarial Networks, CVPR, 2017

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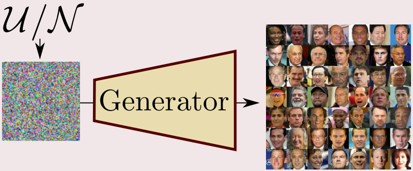
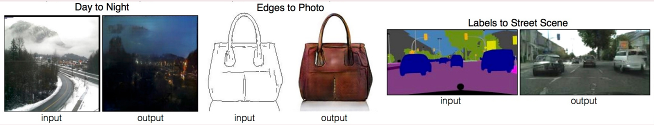


Image-to-Image translation [4]



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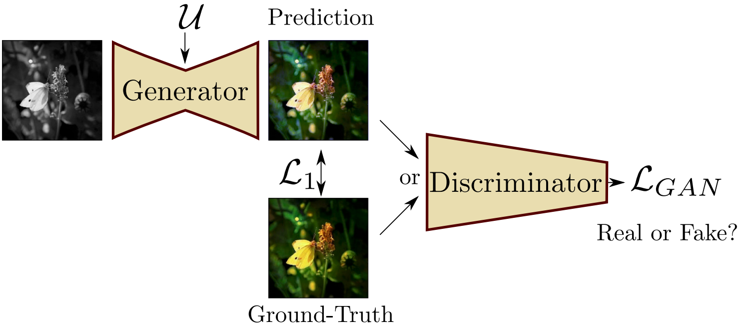


[4] P.Isola, J.-Y.Zhu, T.Zhou, A.A.Efros, Image-to-Image Translation with Conditional Adversarial Networks, CVPR, 2017

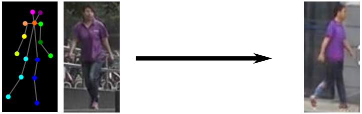
1. **Pose-based Human Image Generation**

2. **Multi-source Generation**

3. **Video generation: Image Animation**

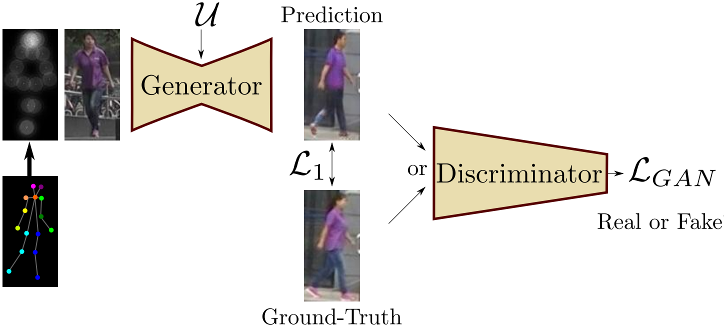
Pose-based Human Image Generation [5]

Prediction

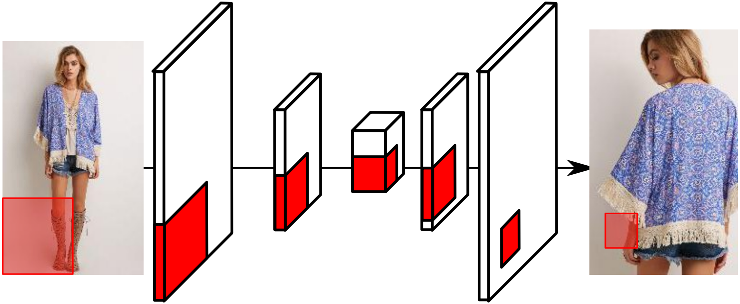


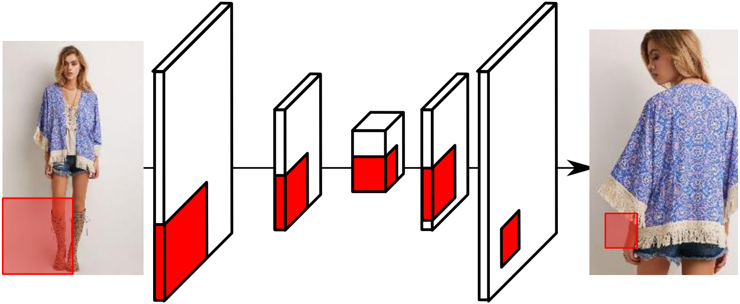
[5] L. Ma, X. Jia, Q. Sun, B. Schiele, T. Tuytelaars, and L. Van Gool, Pose-guided person image generation, NIPS, 2017

Pose-based Human Image Generation [5]



[5] L. Ma, X. Jia, Q. Sun, B. Schiele, T. Tuytelaars, and L. Van Gool, Pose-guided person image generation, NIPS, 2017

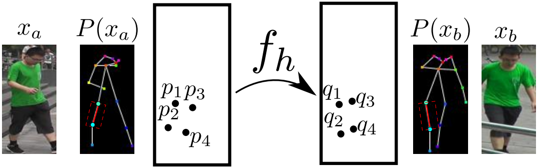




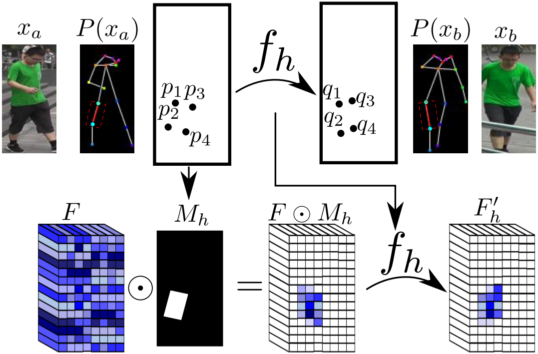
We need a deformation model!

Pose-based Human Image Generation: Our Proposal [6]

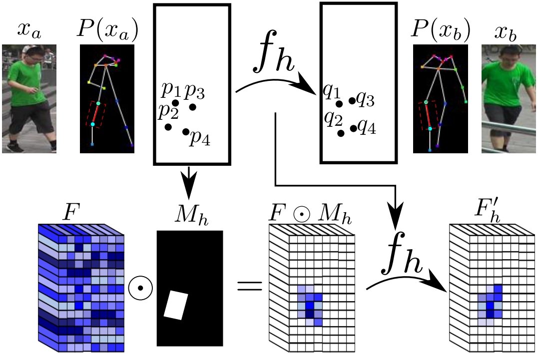
[6] A. Siarohin, E. Sangineto, **S. Lathuilière**, N. Sebe, Deformable GANs for Pose-based Human Image Generation, CVPR, 2018



[6] A. Siarohin, E. Sangineto, **S. Lathuilière**, N. Sebe, Deformable GANs for Pose-based Human Image Generation, CVPR, 2018



[6] A. Siarohin, E. Sangineto, **S. Lathuilière**, N. Sebe, Deformable GANs for Pose-based Human Image Generation, CVPR, 2018



The body parts are combined:

$$d(F) = max_{h=1,\ldots,10} F'_h, \quad (1)$$

[6] A. Siarohin, E. Sangineto, **S. Lathuilière**, N. Sebe, Deformable GANs for Pose-based Human Image Generation, CVPR, 2018

- $\mathcal{L}_1$ and $\mathcal{L}_2$ produce blurred images.

We propose a *nearest-neighbour* loss $\mathcal{L}_{NN}$

- Compute in a feature space $g(x)$.
- $g(\cdot)$: externally trained network.

$$\mathcal{L}_1^g(\hat{x}, x_b) = \sum_{\mathbf{p} \in g(\hat{x})} ||g(\hat{x})(p) - g(x_b)(p)||_1, \tag{2}$$

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$$\mathcal{L}_{NN}(\hat{x}, x_b) = \sum_{\mathbf{p} \in g(\hat{x})} min_{\mathbf{q} \in \mathcal{N}(\mathbf{p})} ||g(\hat{x})(\mathbf{p}) - g(x_b)(\mathbf{q})||_1, \quad (3)$$

- where $\mathcal{N}(\mathbf{p})$ is a $n \times n$ local neighbourhood of point $\mathbf{p}$

Pose-based Human Image Generation: ablation

x_a Target pose GT *Baseline* *Def.* *Full*

Figure: Qualitative results on the Market-1501 dataset.

Pose-based Human Image Generation: ablation

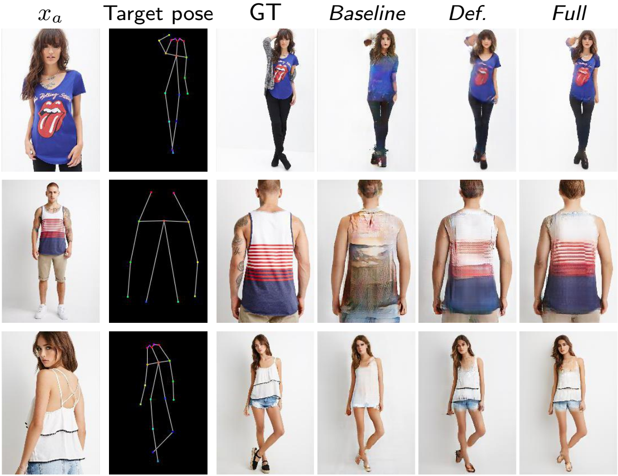

Figure: Qualitative results on the DeepFashion dataset.

Table: Comparison with the state of the art on the DeepFashion dataset.

Model	*SSIM*	*IS*
Ma et al. [7]	0.762	3.090
Ma et al. [8]	0.614	3.228
Esser et al. [9]	**0.786**	3.087
Ours	0.756	**3.439**

[7] L. Ma, X. Jia, Q. Sun, B. Schiele, T. Tuytelaars, and L. Van Gool, Pose-guided person image generation, NIPS, 2017
[8] L. Ma, Q. Sun, S. Georgoulis, L. Van Gool, B. Schiele, and M. Fritz, Disentangled person image generation, CVPR, 2018
[9] P. Esser, E. Sutter, and B. Ommer, A variational u-net for conditional appearance and shape generation, CVPR, 2018

	IDE + Euclidean [10] *Rank 1*	Discr. Embedding [11] *Rank 1*
No augmentation	73.9	78.3

Table: Data augmentation for Re-ID on the Market-1501 (*Rank 1* in %).

[7] L.Ma, X.Jia, Q.Sun, B.Schiele, T.Tuytelaars, and L.Van Gool, Pose-guided person image generation, NIPS, 2017

[9] P. Esser, E. Sutter, and B. Ommer, A variational u-net for conditional appearance and shape generation, CVPR, 2018

[10] L.Zheng, Y.Yang, and A.G.Hauptmann, Person re-identification: Past, present and future, arXiv, 2016

[11] Z. Zheng, L. Zheng, and Y. Yang, A discriminatively learned CNN embedding for person reidentification, TOMCCAP, 2018

[12] A. Siarohin, **S. Lathuilière**, E. Sangineto, N. Sebe, Appearance and Pose-Conditioned Human Image Generation using Deformable GANs, TPAMI, 2019

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Ours (Full) [12]	**78.9**	**81.4**

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[10] L.Zheng, Y.Yang, and A.G.Hauptmann, Person re-identification: Past, present and future, arXiv, 2016

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	IDE + Euclidean [10] *Rank 1*	Discr. Embedding [11] *Rank 1*
No augmentation	73.9	78.3
Ours (Full) [12]	**78.9**	**81.4**
Ours (Baseline)	68.1	70.6
Ma et al. [7]	66.9	73.9
Esser et al. [9]	58.1	63.1

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[7] L.Ma, X.Jia, Q.Sun, B.Schiele, T.Tuytelaars, and L.Van Gool, Pose-guided person image generation, NIPS, 2017

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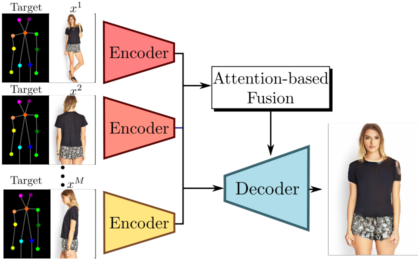
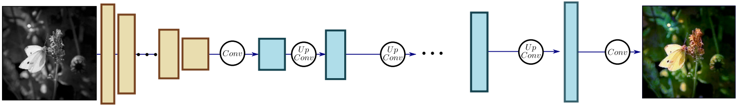


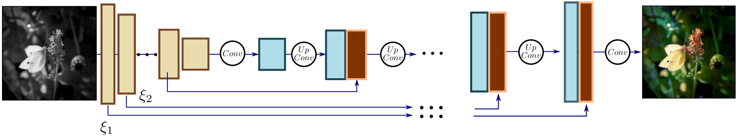
- Multiple input images
- How to select the relevant information in each image depending on:
    - pose difference
    - potential occlusions
    - image quality

[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020

U-Net [14]

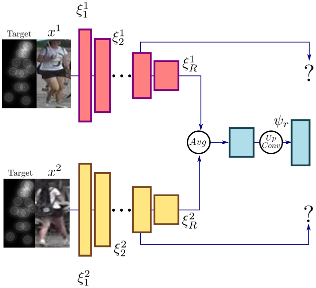


[14] O.Ronneberger, P.Fischer, and T.Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation

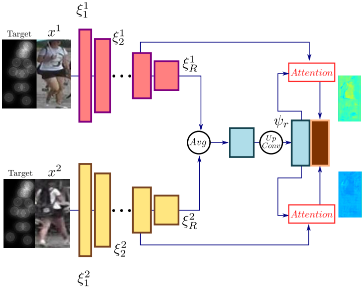


Skip connections

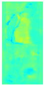
[14] O.Ronneberger, P.Fischer, and T.Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation



[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020

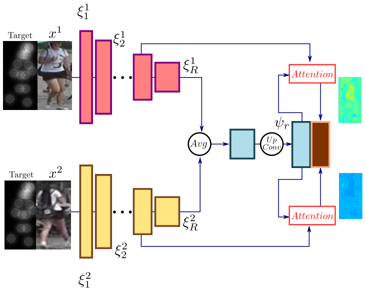


We propose [13]:



$$= \mathit{Att}(\underbrace{\psi_r}_{\text{features}}, \underbrace{\boldsymbol{\xi}_r^i}_{\text{skip connection}})$$

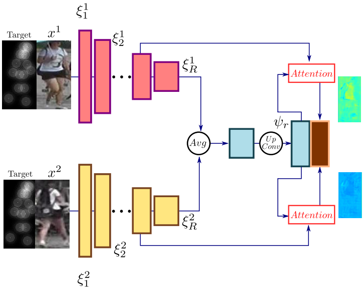
[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020



We propose [13]:

$$\color{red}{Att}\color{black}(\underbrace{\color{blue}{\psi_r}}_{\text{features}}, \underbrace{\boldsymbol{\xi}_r^i}_{\text{skip connection}}) \odot \boldsymbol{\xi}_r^i,$$

[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020



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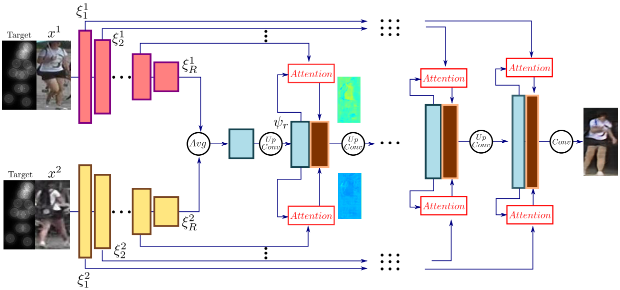
$$F_r = \sum_{i=1}^{M} Att(\underbrace{\psi_r}_{\text{features}}, \underbrace{\boldsymbol{\xi}_r^i}_{\text{skip connection}}) \odot \boldsymbol{\xi}_r^i, \tag{4}$$

[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020



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[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020

Results

Figure: A qualitative evaluation on the Market-1501 dataset.

[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020

Results

Figure: A qualitative evaluation on the Market-1501 dataset.

[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020

Figure: A qualitative evaluation on the Market-1501 dataset.

[13] **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020

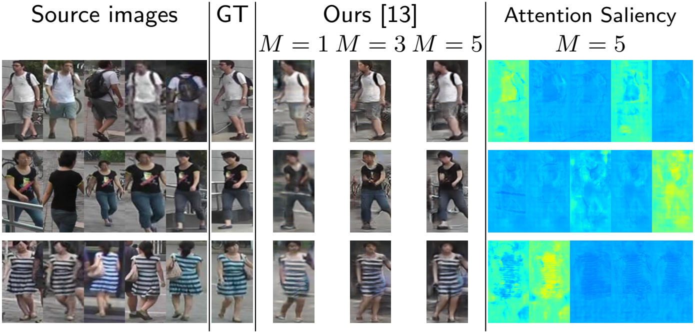

Figure: A qualitative evaluation on the Market-1501 dataset.

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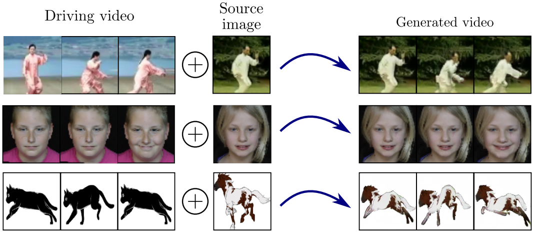

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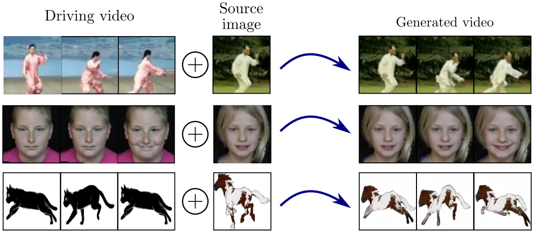
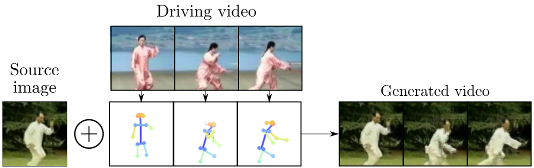
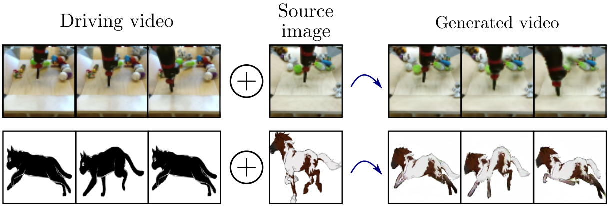


Naive solution: appearance transfer



Problems:

- It requires a detector



[15] A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019

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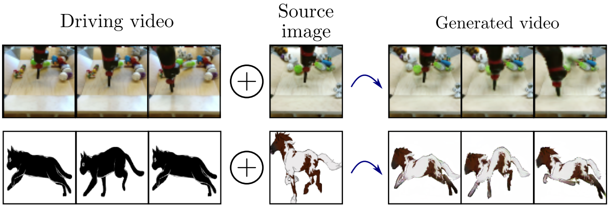
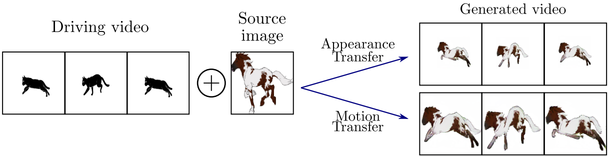


- Does not work when the shapes of the object are different



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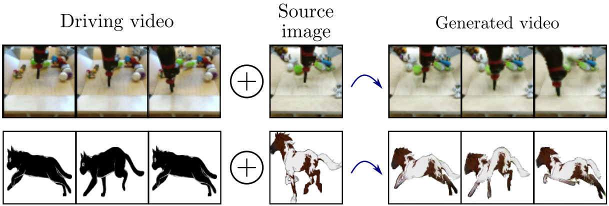

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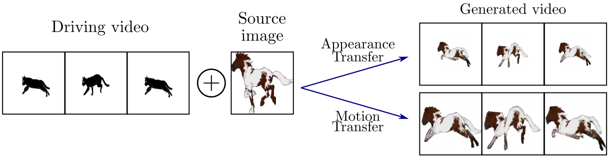
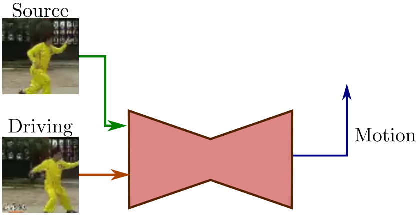


We propose: Self-supervised Motion Transfer [15].

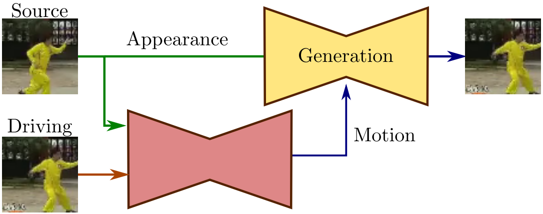
[15] A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019



Self-supervised training.

[15] A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019

Self-supervised Motion Transfer [15]



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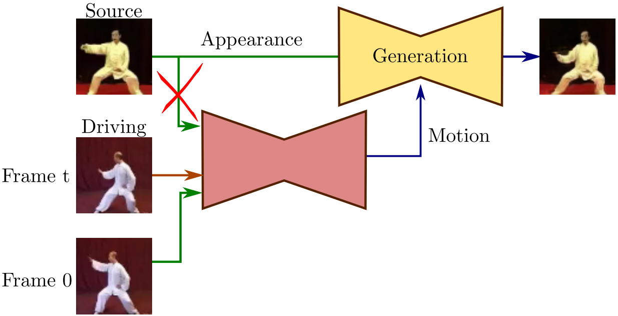
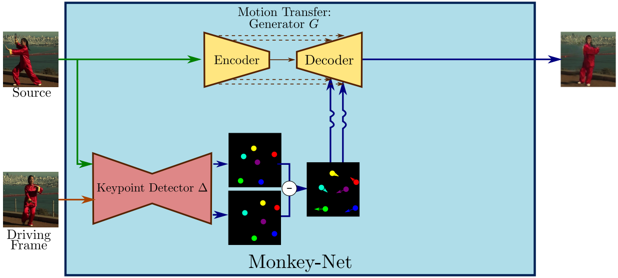


Image animation at test time.

[15] A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019



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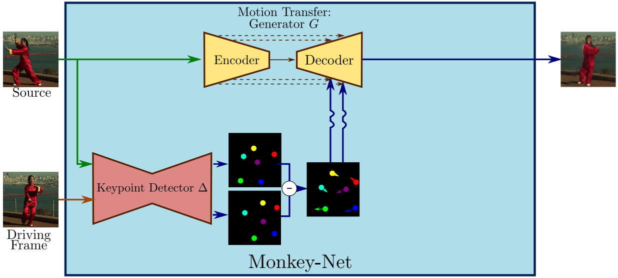

Again, we have an alignment problem.

[15] A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019

Monkey-Net: MOving KEYpoint Network [15]

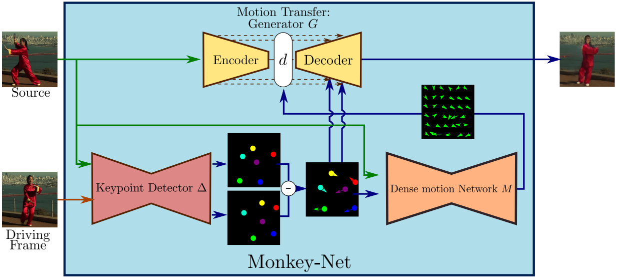

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Image animation: Results

	Tai-Chi			Nemo (Face)			Bair
	$\mathcal{L}_1$	AKD	AED	$\mathcal{L}_1$	AKD	AED	$\mathcal{L}_1$
X2Face [16]	0.068	4.50	0.27	0.022	0.47	0.140	0.069
Ours [15]	**0.050**	**2.53**	**0.21**	**0.017**	**0.37**	**0.072**	**0.025**

Table: Video reconstruction comparisons. We employ *AKD: Average Keypoint Distance* and *AED: Average Euclidean Distance*

[15] A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019

[16] X2Face: A network for controlling face generation by using images, audio, and pose codes. O.Wiles, A.S.Koepke, A. Zisserman, ECCV 2018

	Tai-Chi $\mathcal{L}_1$	*Tai-Chi* AKD	*Tai-Chi* AED	Nemo (Face) $\mathcal{L}_1$	Nemo (Face) AKD	Nemo (Face) AED	Bair $\mathcal{L}_1$
X2Face [16]	0.068	4.50	0.27	0.022	0.47	0.140	0.069
Ours [15]	**0.050**	**2.53**	**0.21**	**0.017**	**0.37**	**0.072**	**0.025**

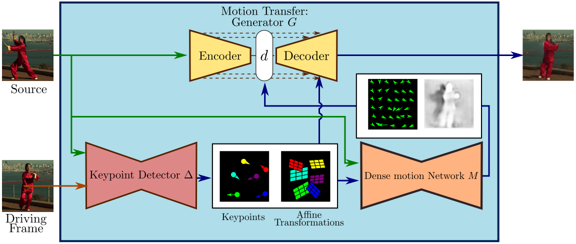
Table: Video reconstruction comparisons. We employ *AKD: Average Keypoint Distance* and *AED: Average Euclidean Distance*

Tai-Chi	*Nemo*	*Bair*
85.0%	79.2%	90.8%

Table: User study results on image animation. Proportion of times our approach is preferred over X2face [16].

[15] A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019

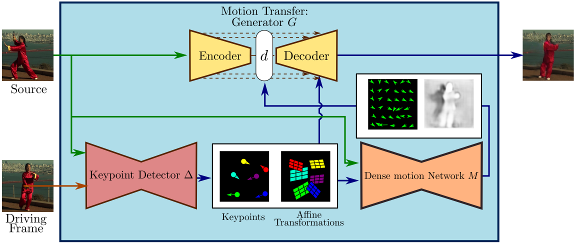
[16] X2Face: A network for controlling face generation by using images, audio, and pose codes. O.Wiles, A.S.Koepke, A. Zisserman, ECCV 2018



$$\mathcal{T}_{\mathbf{X}\leftarrow\mathbf{R}}(p) = \mathcal{T}_{\mathbf{X}\leftarrow\mathbf{R}}(p_k) + o(\|p - p_k\|), \tag{5}$$

[17] A. Siarohin, **S. Lathuilière**, S. Tulyakov, E. Ricci, N. Sebe, First Order Motion Model for Image Animation , NeurIPS 2019

Image animation: after Monkey-Net

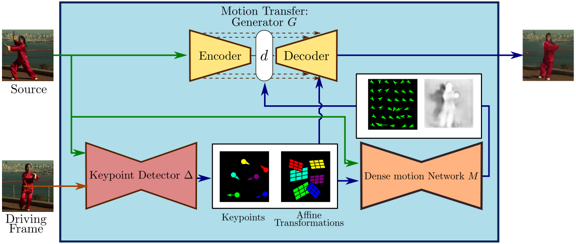


$$\mathcal{T}_{\mathbf{X}\leftarrow\mathbf{R}}(p) = \mathcal{T}_{\mathbf{X}\leftarrow\mathbf{R}}(p_k) + \left(\frac{d}{dp}\mathcal{T}_{\mathbf{X}\leftarrow\mathbf{R}}(p)\Big|_{p=p_k}\right)(p - p_k) + o(\|p - p_k\|), \quad (5)$$

[17] A. Siarohin, **S. Lathuilière**, S. Tulyakov, E. Ricci, N. Sebe, First Order Motion Model for Image Animation , NeurIPS 2019

Image animation: after Monket-Net

Image animation: after Monket-Net



Future works:

- Improve activity recognition methods
- Condition motion on other inputs
- Compression for video call (*e.g.* Skype)

Thank You!
Thanks to Aliaksandr, Sergey, Enver, Elisa and Nicu!

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- A. Siarohin, **S. Lathuilière**, E. Sangineto, N. Sebe, Appearance and Pose-Conditioned Human Image Generation using Deformable GANs, T-PAMI, 2019.
- **S. Lathuilière**, A. Siarohin, E. Sangineto, and N. Sebe, Attention-based Fusion for Multi-source Human Image Generation, WACV 2020
- A. Siarohin, **S. Lathuilière**, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer, CVPR 2019
- A. Siarohin, **S. Lathuilière**, S. Tulyakov, E. Ricci, N. Sebe, First Order Motion Model for Image Animation , NeurIPS 2019