#### Efficient Neural Networks for Real-time Motion Style Transfer

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# Motion Style



https://vimeo.com/26250920



https://tenor.com/view/walk-sad -depressed-lonely-alone-gif-5011387



https://ramminanimation.tumblr.com/post/ 136714032539/angry-walk-cycle

## Goal

Style transfer that works:

Unlabeled, heterogeneous motion sequences

In real-time

With user control

In a computationally and memory efficient way

# **Existing Methods**



Holden, Daniel, et al. "Fast neural style transfer for motion data." *IEEE computer graphics and applications* 37.4 (2017): 42-49.



Mason, Ian, et al. "Few-shot Learning of Homogeneous Human Locomotion Styles." *Computer Graphics Forum*. Vol. 37. No. 7. 2018.



Yumer, M. Ersin, and Niloy J. Mitra. "Spectral style transfer for human motion between independent actions." *ACM Transactions on Graphics (TOG)* 35.4 (2016): 137.



Xia, Shihong, et al. "Realtime style transfer for unlabeled heterogeneous human motion." *ACM Transactions on Graphics (TOG)* 34.4 (2015): 119.

#### Realtime Style Transfer for Unlabeled Heterogeneous Human Motion



Xia, Shihong, et al. "Realtime style transfer for unlabeled heterogeneous human motion." ACM Transactions on Graphics (TOG) 34.4 (2015): 119.





### Overview





550,000 training samples



#### Input Pose Preprocessing

Input pose translated above origin

Rotated to face positive z axis

Concatenated with 5 previous poses, covering last 0.25 seconds

Gaussian normalization







Old Style Vector

Angry Style Vector

Strutting Style Vector



## Output Pose









# Networks and Training

#### **Pose Network**

128 units per layer Mean Squared Error loss

#### **Timing Network**

64 units per layer Mean Squared Error loss

#### **Foot Contact Network**

32 units per layer Binary Cross-Entropy loss

Optimizer: ADAM Learning rate: 0.01 Epochs: 20 Minibatch Size: 64

Implemented in Pytorch Training Time: 3 hours i7 3.5GHz 4-core with Geoforce GTX1070



3x

# **Predicting Input Poses**



## **Results - Locomotion**



#### **Results** -

#### **Heterogeneous Motion**



### Results -Comparison with Original



## **Run-time Performance**

	Memory	FPS	
	Footprint	Achieved	
[Xia et al. 2015]	290 MB	55*	*CUDA + GPU
[Yumer and Mitra 2016]	Not Reported	50	
Our Method (PC)	931 KB	115	i7 3.5GHz CPU

	Memory	Memory Neural Network	
	Footprint	<b>Forward Pass</b>	
Our Method (PC)	931 KB	0.0008s	i7 3.5GHz CPU
Our Method (Mobile)	931 KB	0.002s	iPhone 7 Plus
[Holden et al. 2017b] Cubic	10MB	0.0018s	
[Holden et al. 2017b] Constant	125MB	0.0008s	
[Mason et al. 2018]	126KB*	0.0011s	
[Zhang et al. 2018]	22MB	0.002s	]

#### Interpolation and Extrapolation Example: Childlike



## Strutting Interpolation

#### Strutting Interpolation

## Blending Childlike to Old

#### Blending From Childlike to Old

#### Combining Old and Strutting



#### User Study: Style Recognition

Ours

Xia's





## User Study: Exaggeration



"Which Video is More Expressive of an 'Old' Style?"

## User Study: Extrapolation

Style	Ours	Xia's	Don't Know
Angry	27 (63%)	15 (34%)	1 (3%)
Childlike	33 (77%)	6 (14%)	4 (9%)
Depressed	31 (72%)	12 (28%)	0
Old	37 (86%)	6 (14%)	0
Proud	3 (7%)	40 (93%)	0
Sexy	17 (39%)	25 (58%)	1 (3%)
Strutting	27 (63%)	15 (34%)	1 (3%)

## In Summary



#### A method for style transfer that works:

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## Questions?

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