

Render the Possibilities

SIGGRAPH2016

THE 43RD INTERNATIONAL
CONFERENCE AND EXHIBITION ON

 Computer Graphics
Interactive Techniques

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ANAHEIM, CALIFORNIA



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Computer Graphics
Interactive Techniques



A Deep Learning Framework for Character Motion Synthesis and Editing

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Outline

Motivation

Synthesis

Editing

Discussion

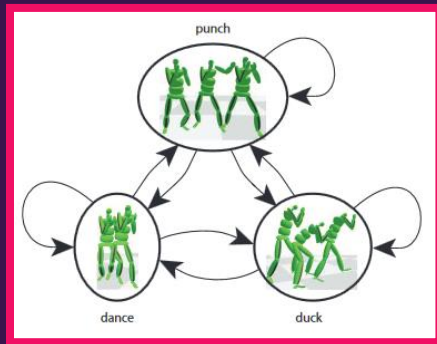
Goal

Data driven synthesis of motion
from high level controls with
no manual preprocessing



Previous Work

- Lots of manual processing (Graphs, Trees)
 - Segmentation
 - Alignment
 - Classification



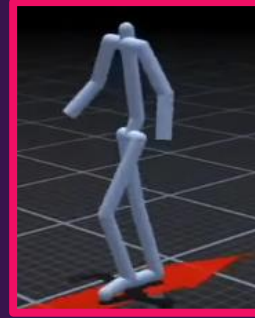
[Heck et al. 2007]



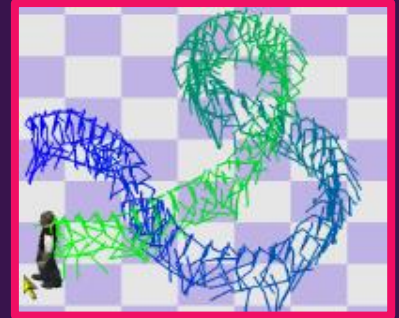
[Kovar et al. 2002]

Previous Work

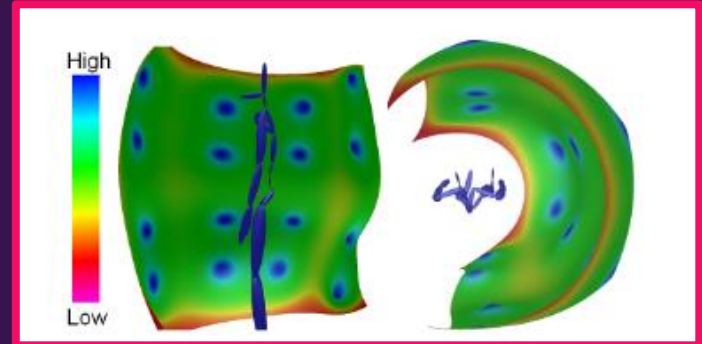
- Scalability Issues (RBF, GP, GPLVM, kNN)
 - Must store whole database in memory
 - Grows $O(n^2)$ with number of data points
 - Requires expensive acceleration structures



[Lee et al. 2010]



[Park et al. 2002]



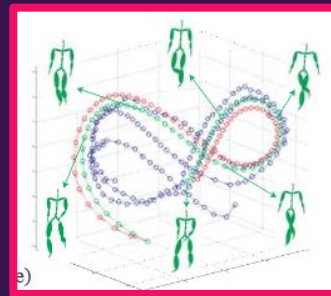
[Mukai and Kuriyama 2005]

Previous Work

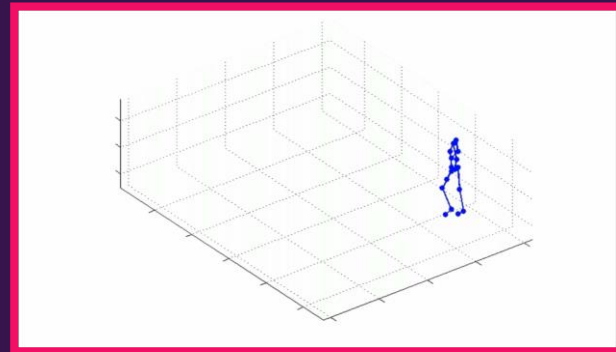
- Instability issues (GPDM, CRBM, RNN)
 - Limited to some classes of motion
 - Can suffer high frequency noise or “dying out”



[Levine et al. 2012]



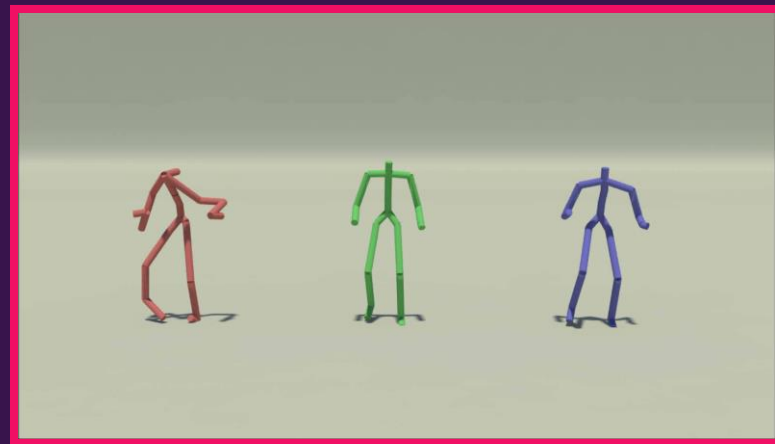
[Wang et al. 2005]



[Taylor et al. 2011]

Previous Work

- Deep Neural Network
Hidden Units used to represent motion
 - Denoising
 - Retrieval
 - Interpolation



[Holden et al. 2015]

Previous Work

- Deep Learning not always ready for production
- Results can look strange

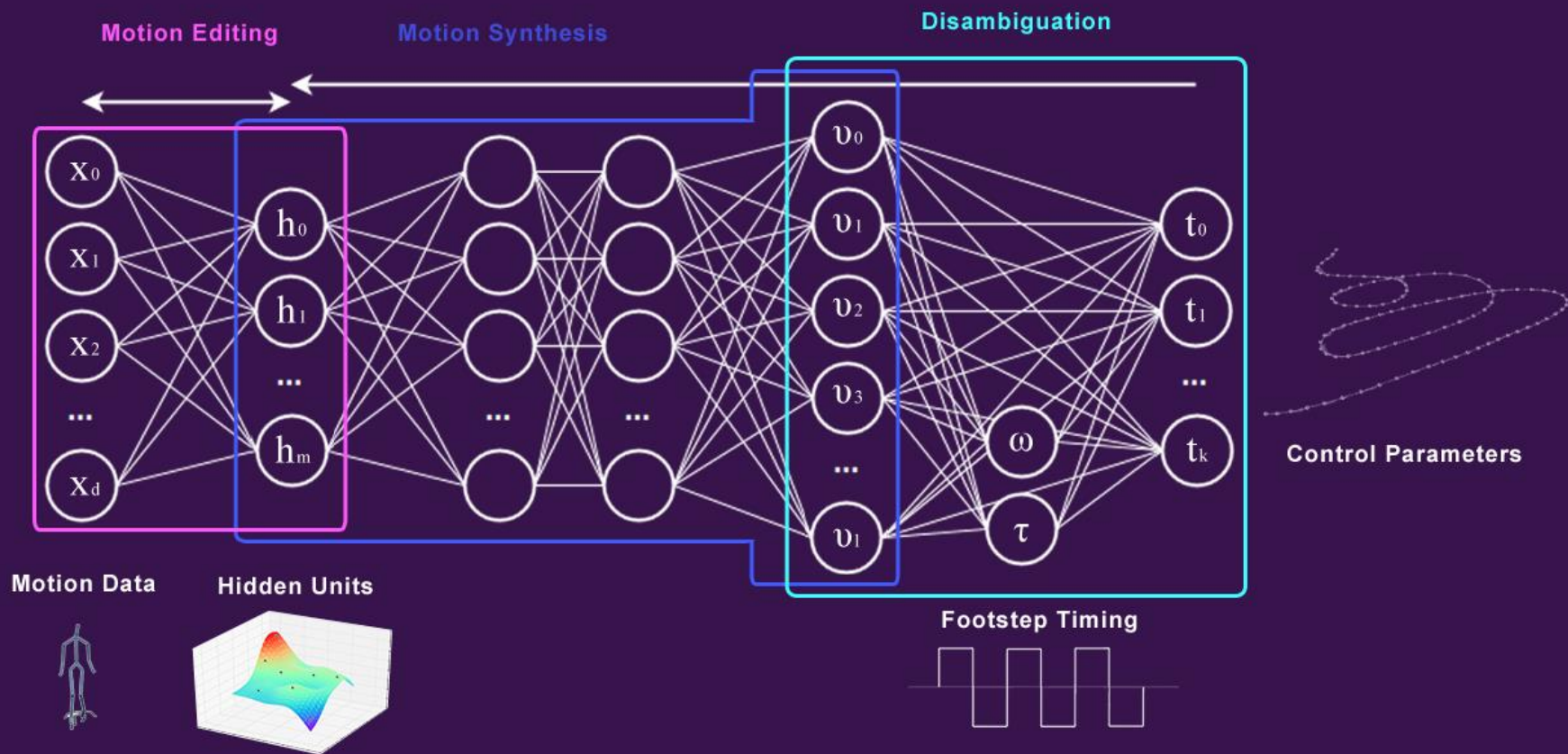


[Radford et al. 2015]

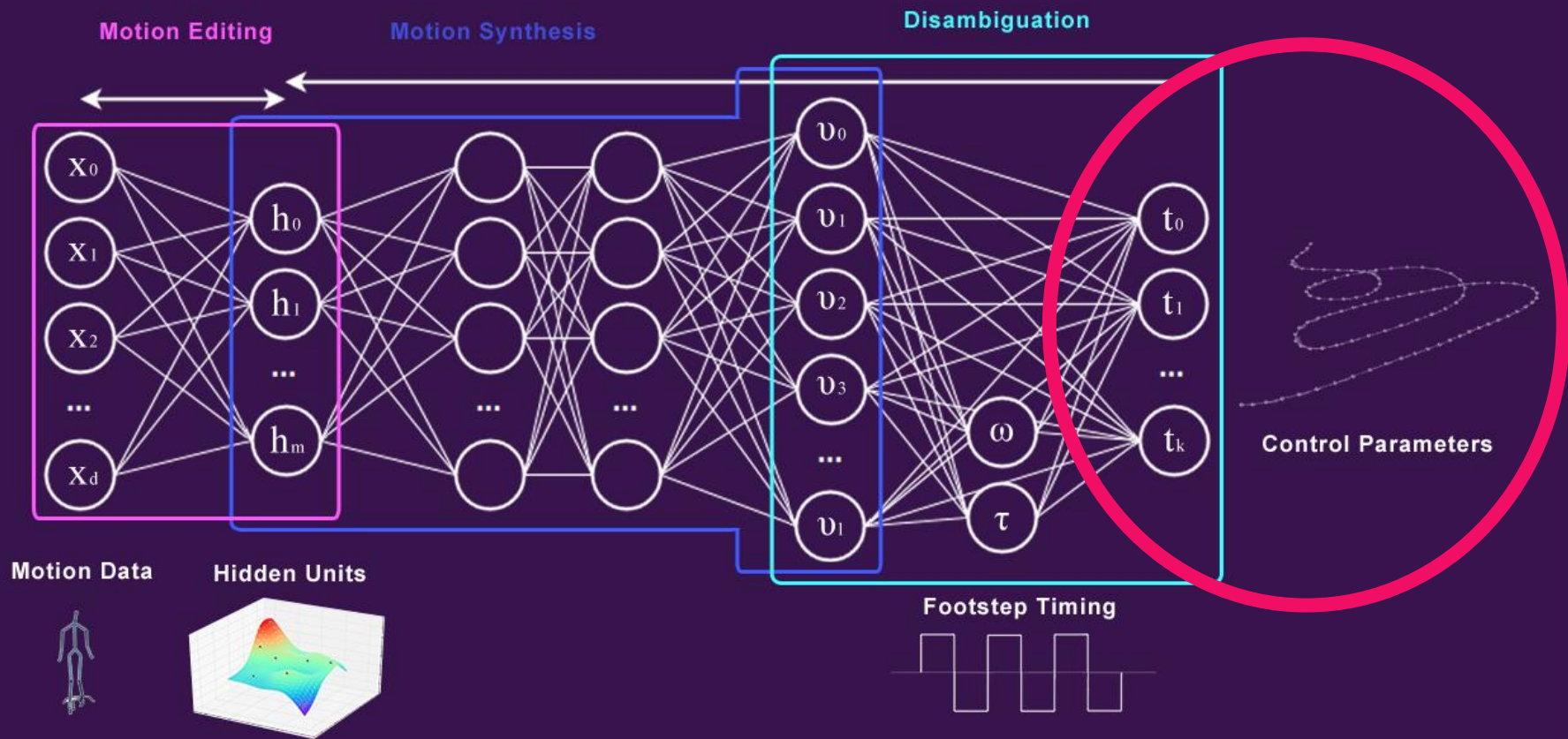
Contribution

- **High quality synthesis with no manual preprocessing**
- Motion synthesis and editing in **unified framework**
- **Procedural, parallel** technique

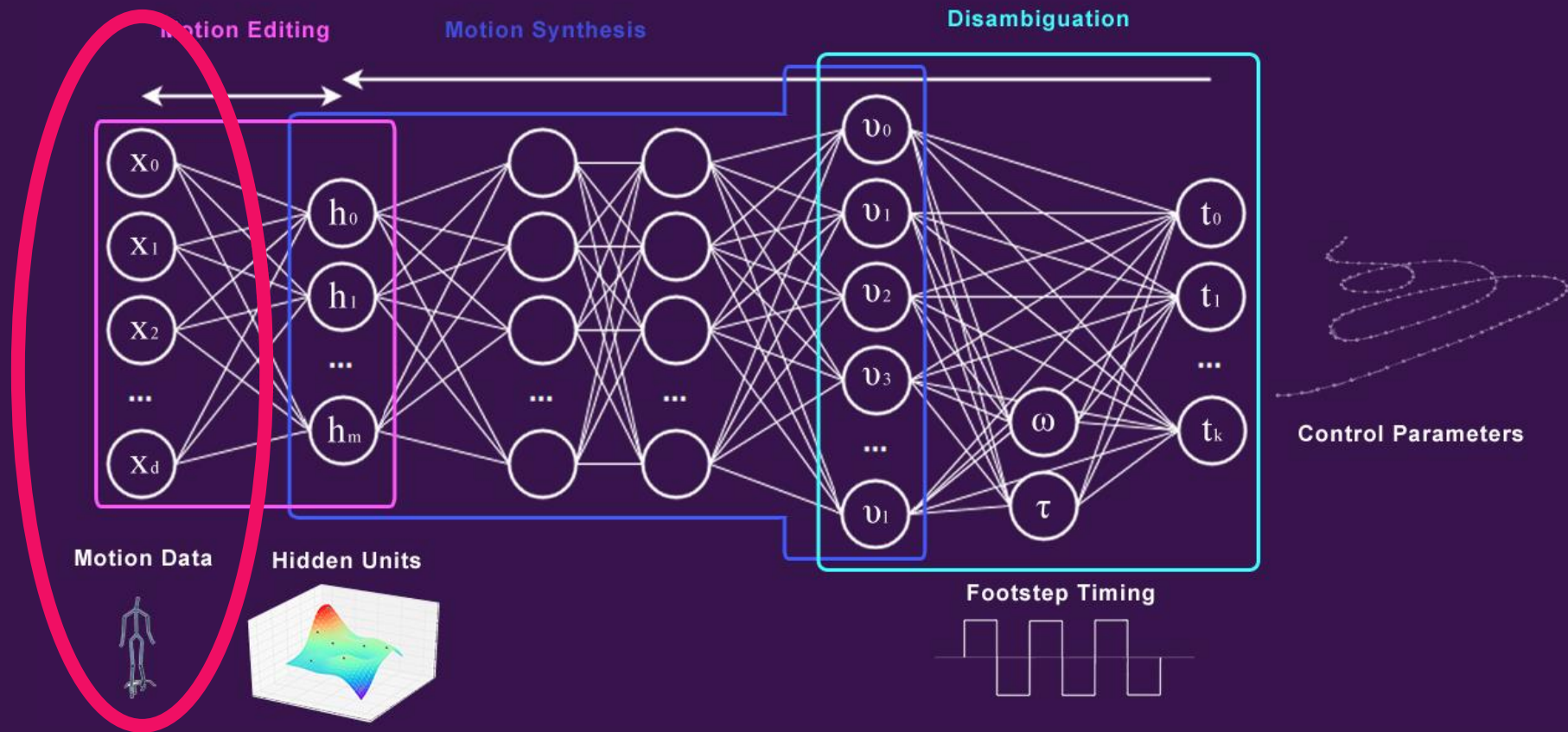
Overview



Overview



Overview



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Synthesis

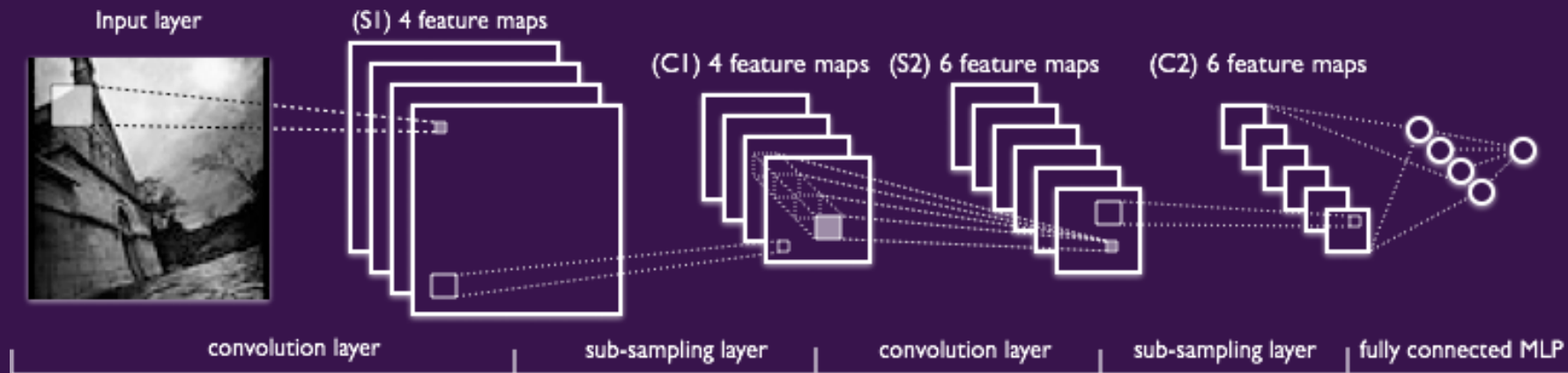
Editing

Discussion



Convolutional Neural Networks

- Great success in classification and segmentation for images, video, sound
- We can use CNN on motion data too



Convolution

Filters convolve over temporal dimension



Convolution

Filters convolve over temporal dimension



Convolution

Filters convolve over temporal dimension



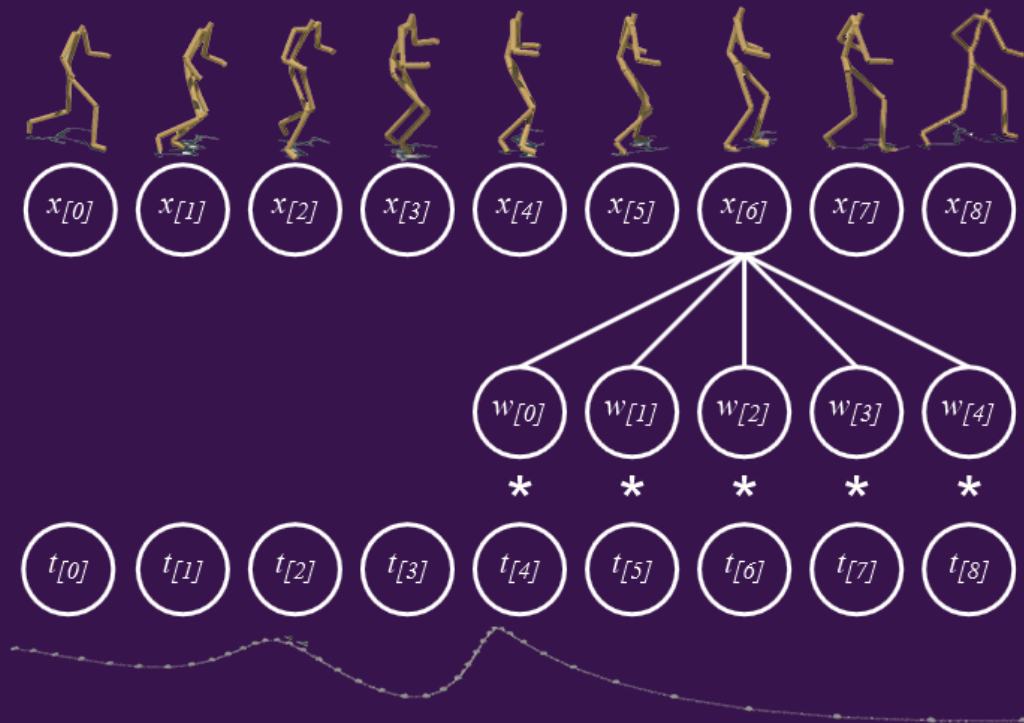
Convolution

Filters convolve over temporal dimension



Convolution

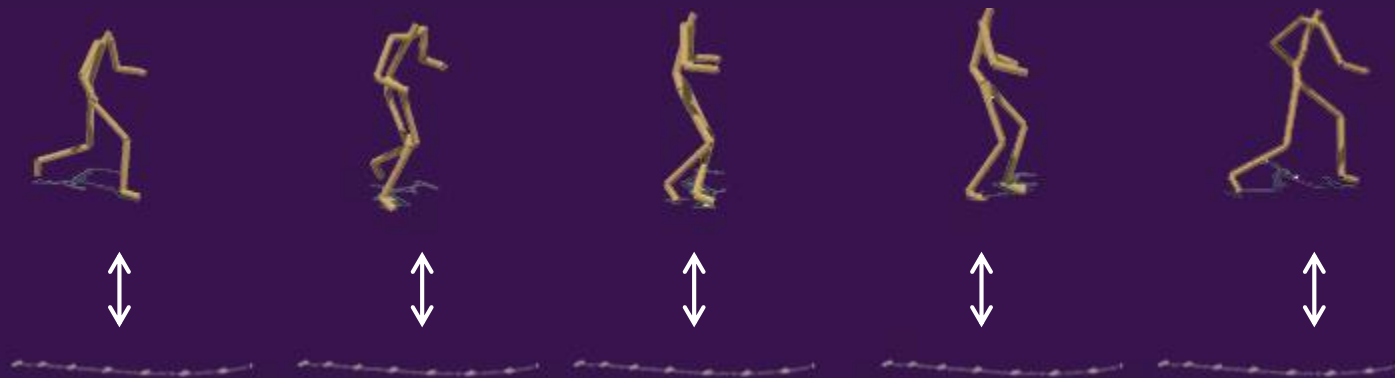
Filters convolve over temporal dimension





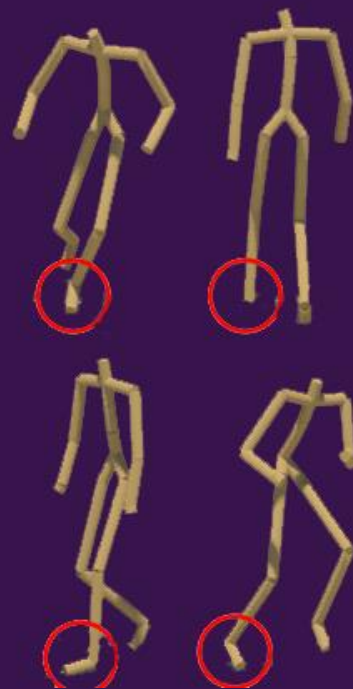
What Happened?

- **Ambiguity:** the same control signal maps to multiple motions
- These motions are averaged in the output



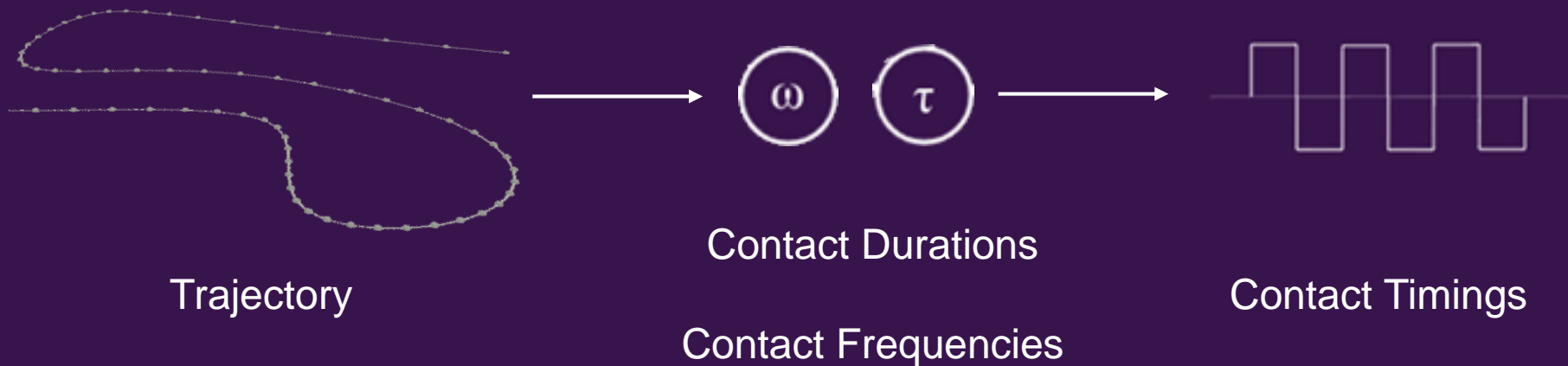
Foot Contact

- Contact times resolve ambiguity
- Automatically label using foot speed and height
- Learn model that generates contact times from trajectory

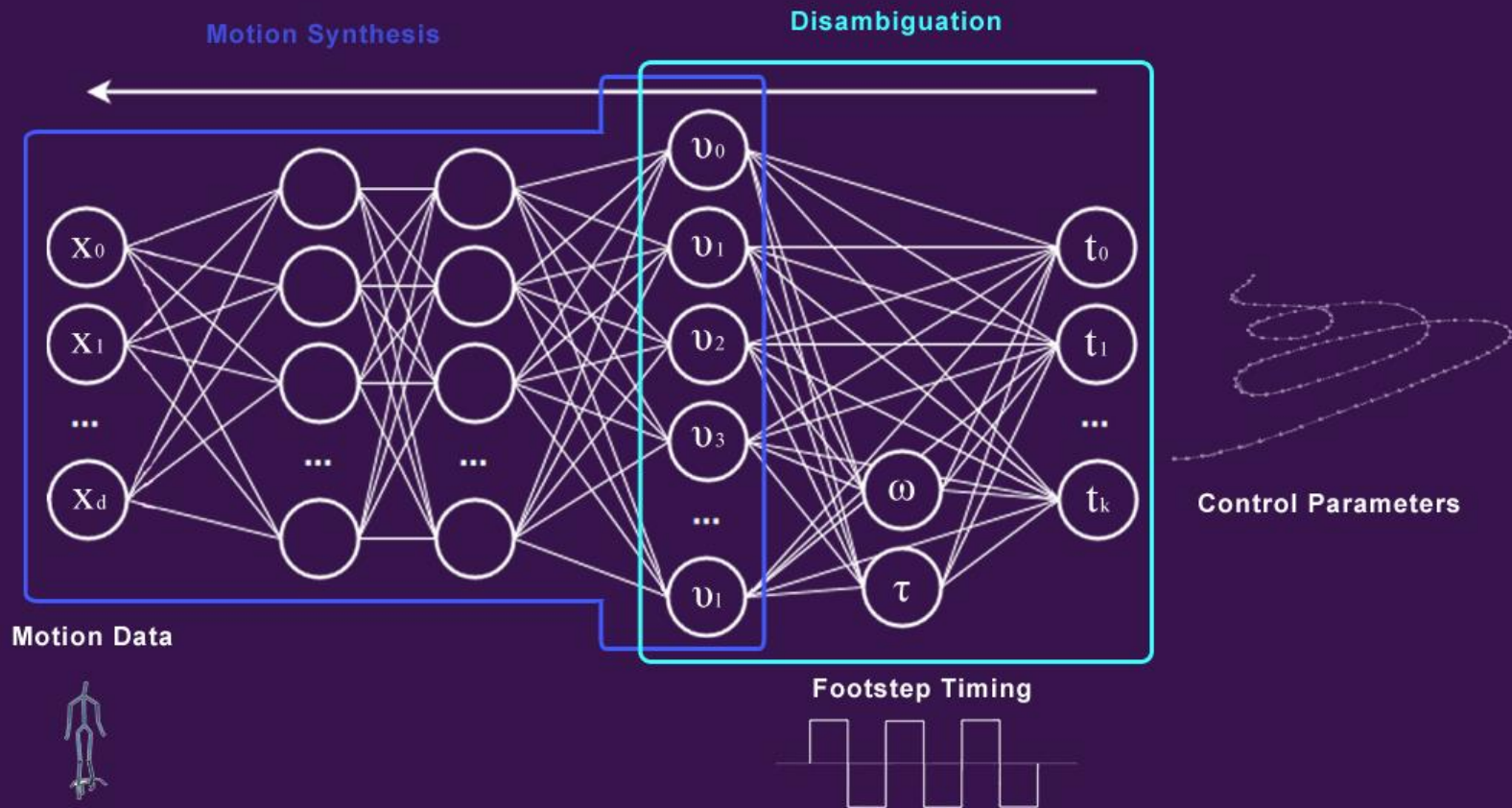


Foot Contact

- Use small neural network to map trajectories to contact durations and frequencies
- Produce timings from durations and frequencies



Overview





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Motion Editing

Once motion is generated it must be edited



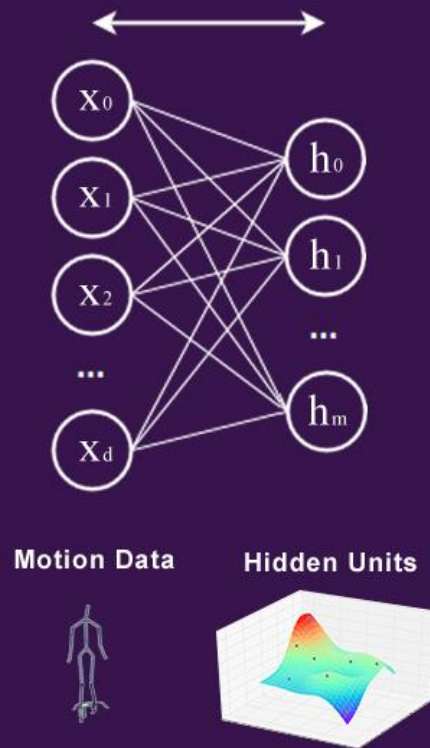
Motion Editing

Post processing may not ensure naturalness



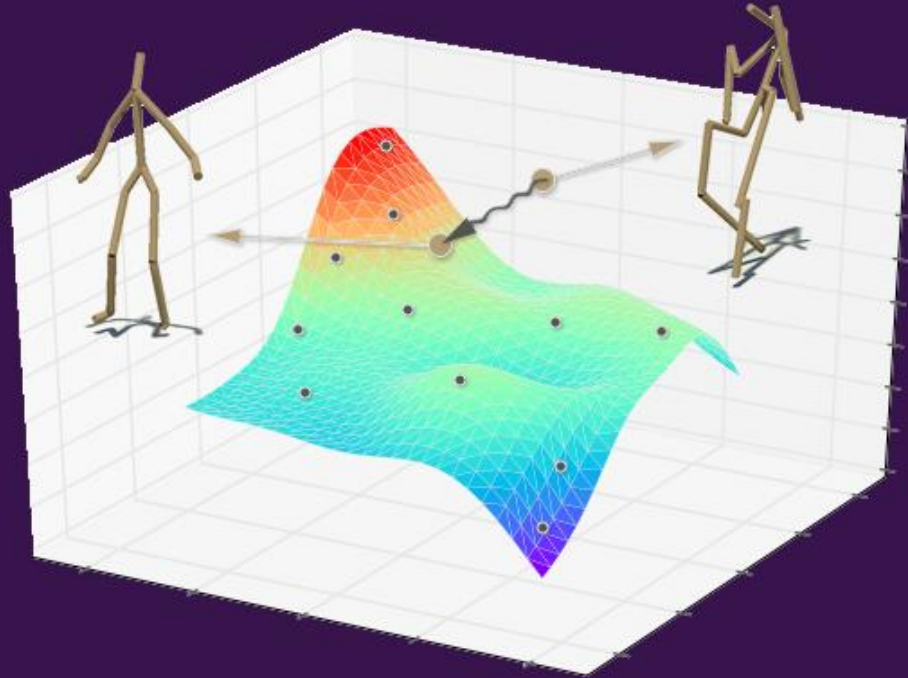
Motion Editing

- We edit using the motion manifold learned by a Convolutional Autoencoding Network [Holden et al. 2015]



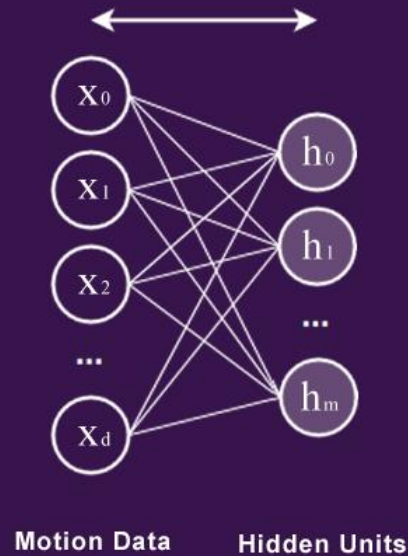
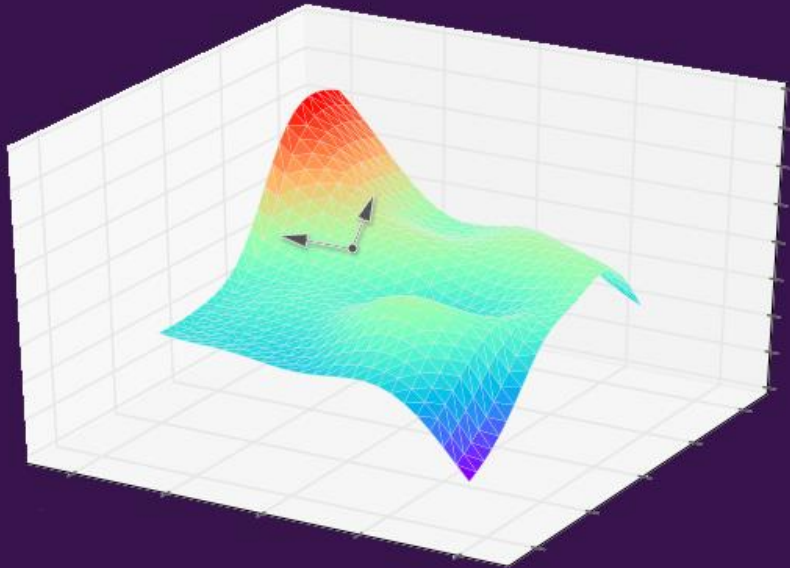
Autoencoder

- Learns *projection operator* of motion manifold



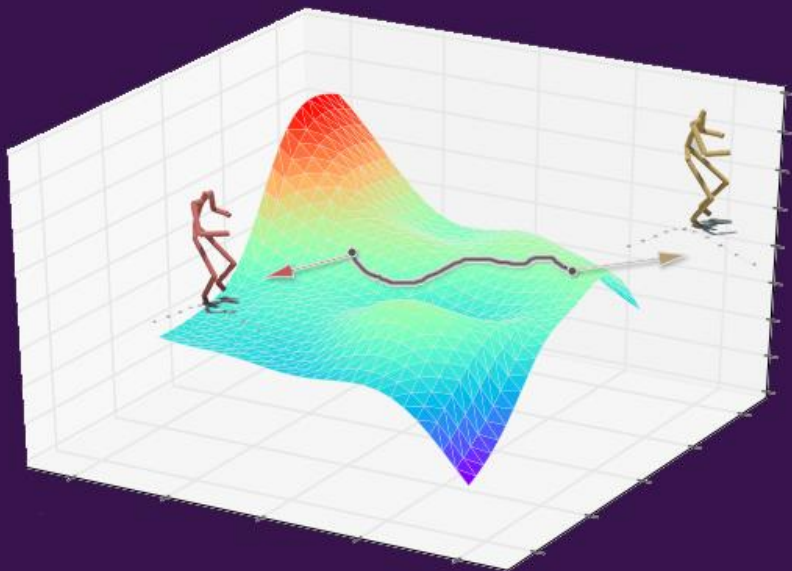
Manifold Surface

- *Hidden Unit* values parametrise manifold surface
- Adjusting them ensures motion remains natural



Constraint Satisfaction

- Motion editing is a *constraint satisfaction problem over Hidden Units*



Motion Data

Hidden Units

Constraint Satisfaction

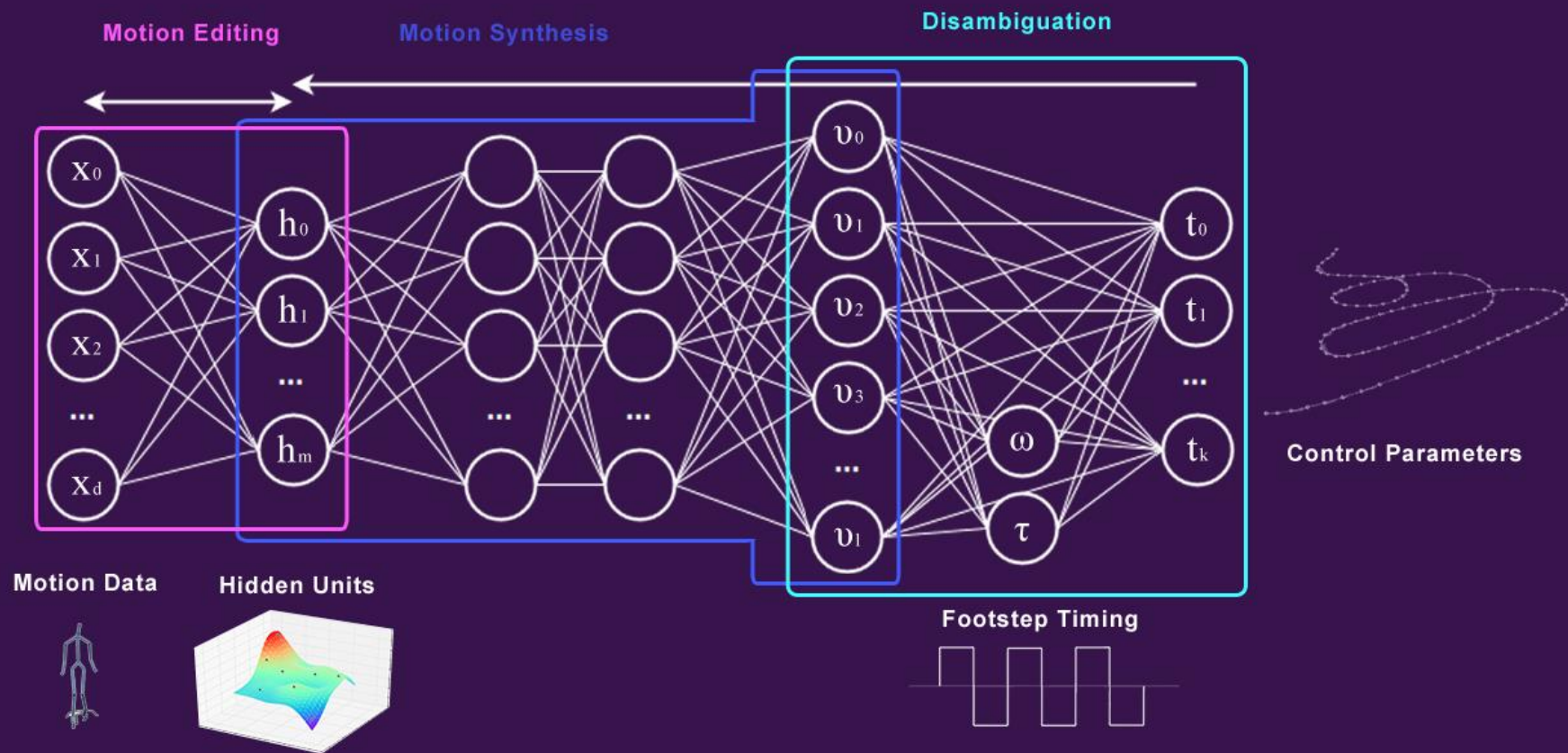
- Local foot velocity must equal global velocity

$$Pos(\mathbf{H}) = \sum_j \|\mathbf{v}_r^{\mathbf{H}} + \boldsymbol{\omega}^{\mathbf{H}} \times \mathbf{p}_j^{\mathbf{H}} + \mathbf{v}_j^{\mathbf{H}} - \mathbf{v}_j'\|_2^2.$$

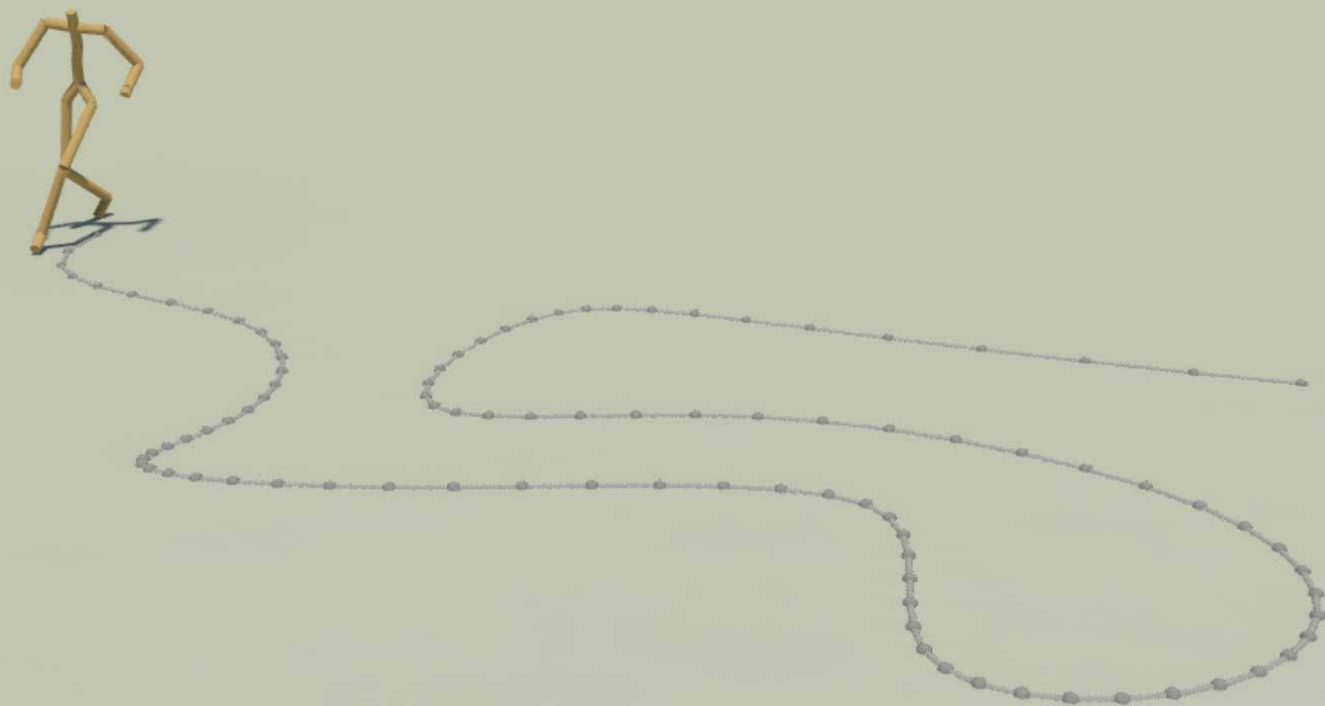
- Output trajectory must equal input trajectory

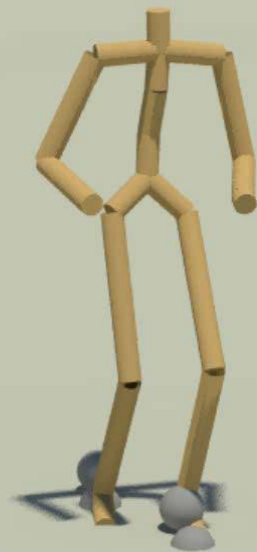
$$Traj(\mathbf{H}) = \|\boldsymbol{\omega}^{\mathbf{H}} - \boldsymbol{\omega}'\|_2^2 + \|\mathbf{v}_r^{\mathbf{H}} - \mathbf{v}_r'\|_2^2$$

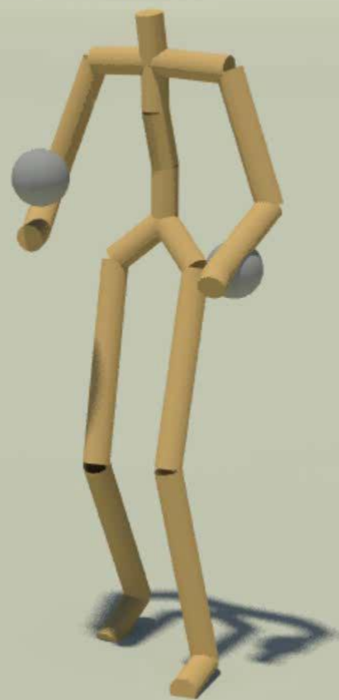
Overview



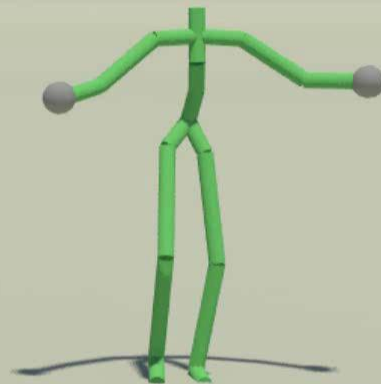












A Neural Algorithm of Artistic Style

- Combine style of one image with content of another [Gatys et al. 2015]



Style Constraint

- Gram Matrix of *Hidden Units* encode style
- Actual Values of *Hidden Units* encode content

$$Style(\mathbf{H}) = s\|G(\Phi(\mathbf{S})) - G(\mathbf{H})\|_2^2 + c\|\Phi(\mathbf{C}) - \mathbf{H}\|_2^2$$

$$G(\mathbf{H}) = \frac{\sum_i^n \mathbf{H}_i \mathbf{H}_i^T}{n}$$

- **No correspondence between clips required!**

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Content Term

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Gram Matrix

- **No correspondence between clips required!**

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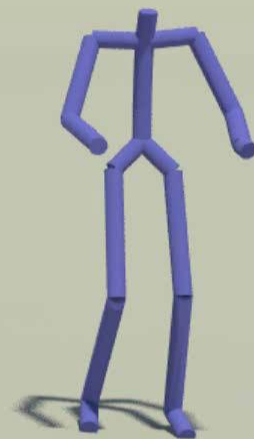
Style



Content



Transfer



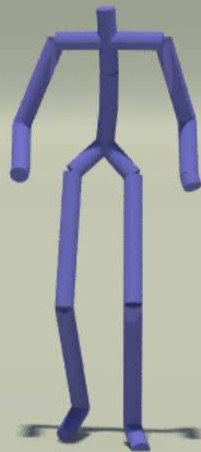
Style



Content



Transfer



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Representation

- We use joint positions local to hip
- Global rotation / translation removed using hips and shoulders direction
- Root velocity and contact times appended to representation



Training

- **Motion Manifold**
 - Several large databases (including whole CMU)
 - Training takes around 6 hours
- **Motion Synthesis**
 - Task specific data only (e.g. locomotion only)
 - Training takes around 1 hour

Procedural vs Simulated

- **Procedural**

- Output computed at arbitrary times or in parallel
- Ideal for precise animation

- **Simulated**

- Output computed frame by frame in series
- Ideal for interactive applications

Performance

- Using GPU system runs in parallel over frames
- Very fast for long motions or many characters

Task	Duration	Foot Contacts	Synthesis	Editing	Total	FPS
Walking	60s	0.025s	0.067s	1.096s	1.188s	3030
Running	60s	0.031s	0.073s	1.110s	1.214s	2965
Punching	4s	-	0.019s	0.259s	0.278s	863
Kicking	4s	-	0.020s	0.302s	0.322s	745
Style Transfer	8s	-	-	2.234s	2.234s	214
Crowd Scene	10s	0.557s	1.335s	2.252s	4.144s	28957

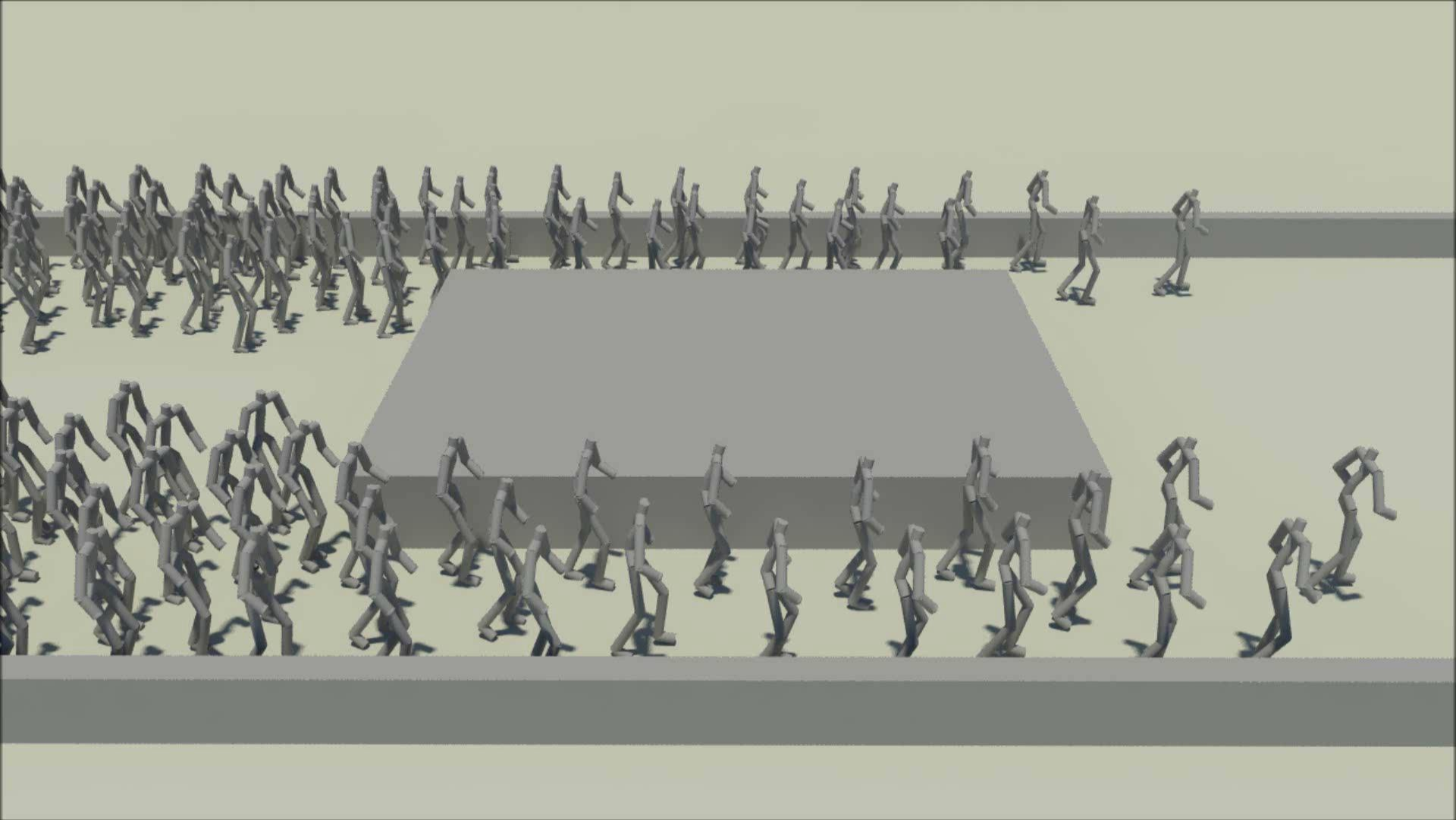
Figure 13: *Performance breakdown.*

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Figure 13: *Performance breakdown.*



Future Work

- Need more general solution for ambiguity issue
- Wish to use more high level features with a deeper network
- What changes are required for interactive applications?

