NeuroAnimator

Fast Neural Network Emulation and Control of Physics-Based Models

Radek Grzeszczuk [1]

Demetri Terzopoulos [2,1]

Geoffrey Hinton [2]

[1] ***Intel Corporation***
Microcomputer Research Lab

[2] ***University of Toronto,***
Dept. of Computer Science

International Conference Graphicon 1998, Moscow, Russia, http://www.graphicon.ru/

Physics-Based Animation

Animation through physical simulation

- Inanimate objects:
  - *rigid models* *(Hahn88, Baraff89)*
  - *articulated models* *(Barzel88)*
  - *deformable models* *(Terzopoulos87, Platt88)*
- Animate objects:
  - *animal models* *(Miller88, Tu95)*
  - *human models* *(Armstrong85, Wilhelms87, Hodgins95,)*

- Pioneering work

Physics-based Models

Simulate Newtonian mechanics

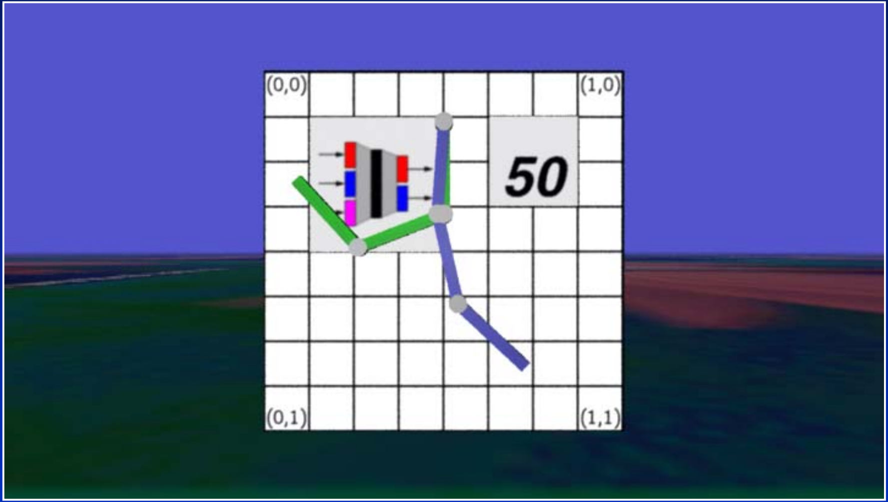
- Benefits
  - *offer unsurpassed realism*
  - *automate motion synthesis*
- Drawbacks
  - *incur high computational costs*
  - *difficult & expensive to control*
- Moore’s Law is on our side!

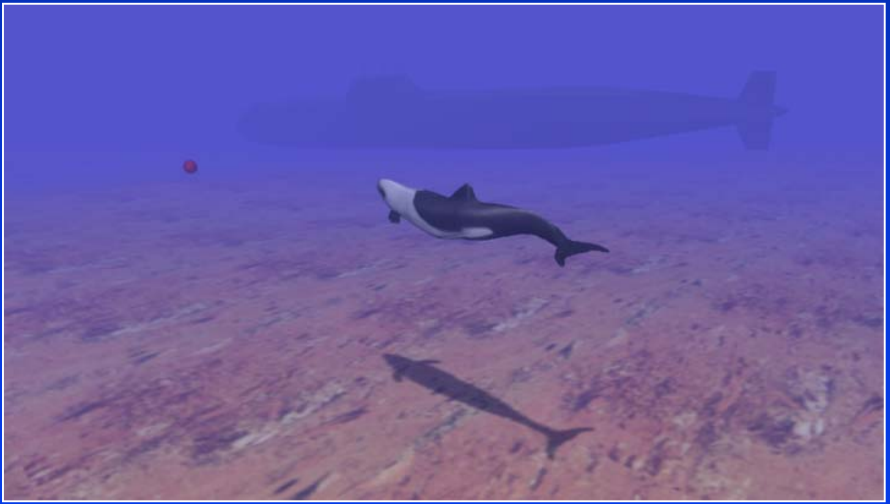
NeuroAnimator

A neural network approach to physically realistic animation

- Learns to approximate physical models by observing their actions
- Yields outstanding efficiency
  - *fast synthesis of physically realistic motion*
  - *fast synthesis of motion controllers for animation*

Example NeuroAnimators





Motivation

Is there a more efficient alternative to animation by simulation?

- Numerical simulation of a dynamical system evaluates a high-dimensional map Φ at every timestep
- In principle (Cybenko89), neural networks can learn to approximate arbitrary, complex maps Φ
- NeuroAnimator: accurate and efficient neural network approximation of maps Φ associated with physics-based CG models

Motivation

Animation through numerical simulation

- Discrete-time dynamical systems

Map

$$\mathbf{s}_{t+\delta t} = \Phi(\mathbf{s}_t, \mathbf{u}_t, \mathbf{f}_t)$$

State

$\mathbf{s} = [\mathbf{x}\ \mathbf{v}]$

Controls

External Forces

- Example:

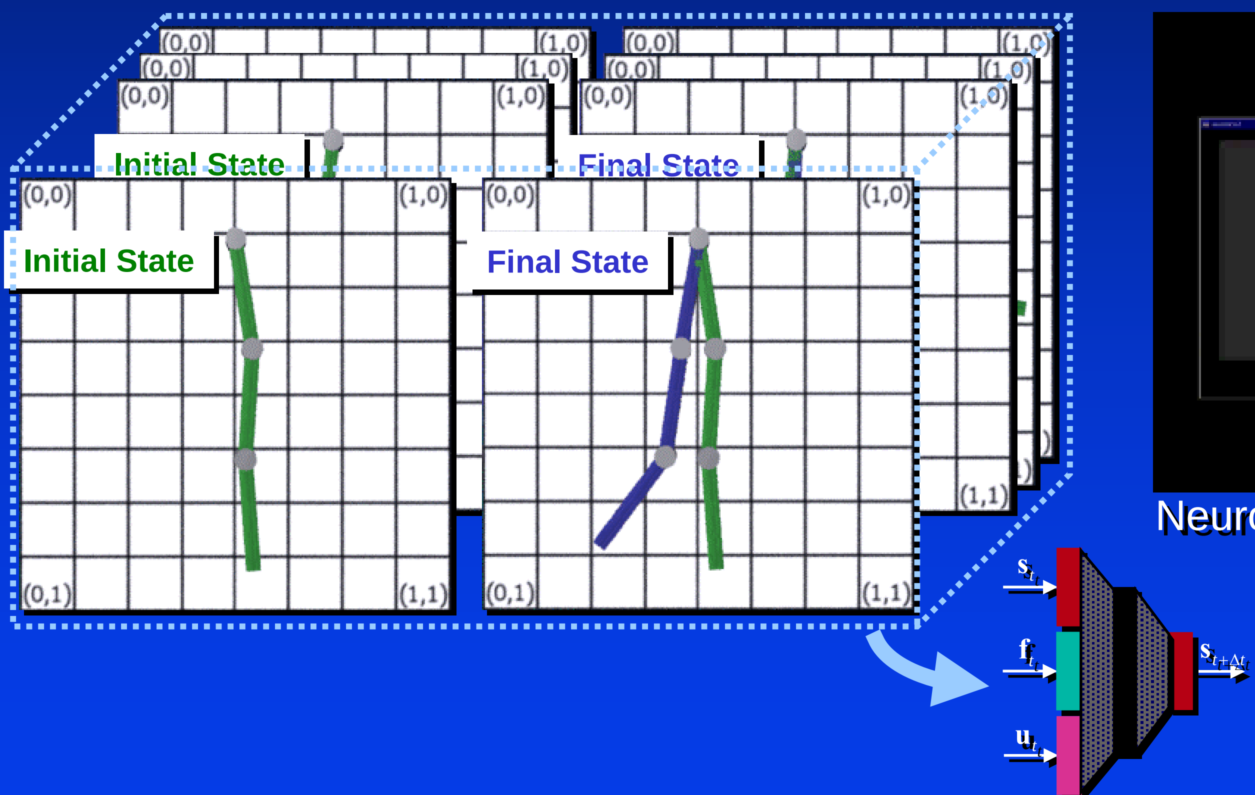
  Implicit Euler time-integration method

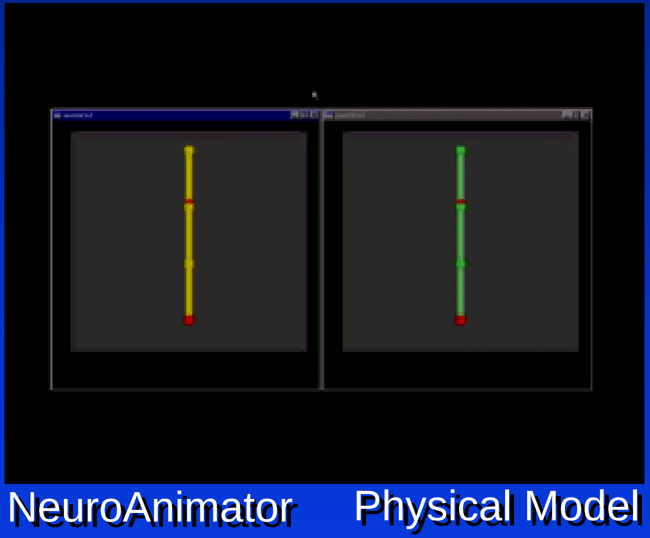
$$\begin{cases} \mathbf{A}_t \mathbf{v}_{t+\delta t} = \mathbf{v}_t + \mathbf{g}(\mathbf{u}_t, \mathbf{f}_t) \\ \mathbf{x}_{t+\delta t} = \mathbf{v}_t \delta t + \mathbf{x}_t \end{cases}$$

$\mathbf{s}_{t+\delta t}$ $\mathbf{s}_t$

Learning Dynamics

The NeuroAnimator learns dynamics by observing sample state transitions





Emulation

super timestep
$\Delta t = n\,\delta t$

NeuroAnimator approximation of Φ

$$\mathbf{s}_{t+\Delta t} = \mathbf{N}_{\Phi}(\mathbf{s}_t, \mathbf{u}_t, \mathbf{f}_t)$$

Why is the NeuroAnimator efficient?

- The emulation step is relatively cheap
- The NeuroAnimator can emulate super timesteps
  - *up to 100 times faster than numerical simulation*
- $\mathbf{N}_{\Phi}$ is analytically differentiable
  - *dramatic efficiency for animation controller synthesis*

Talk Overview

- Introduction
- Artificial neural networks
- From physical models to NeuroAnimators
- NeuroAnimator based controller synthesis
- Conclusion and future work

Talk Overview

- Introduction
- Artificial neural networks
- From physical models to NeuroAnimators
- NeuroAnimator based controller synthesis
- Conclusion and future work

Neural Networks

Seminal work in the field

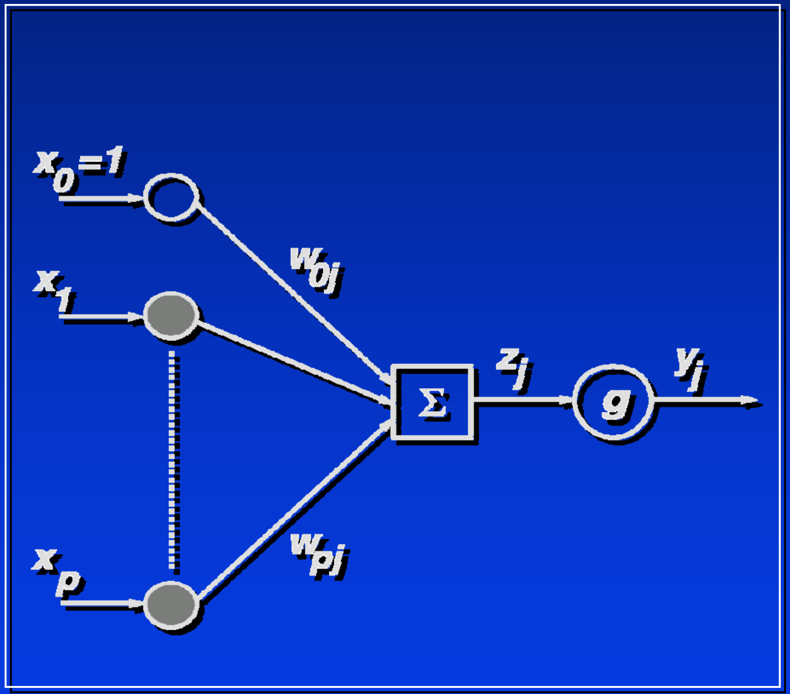
- Perceptrons

  (Widrow60, Rosenblatt62, Minsky69)

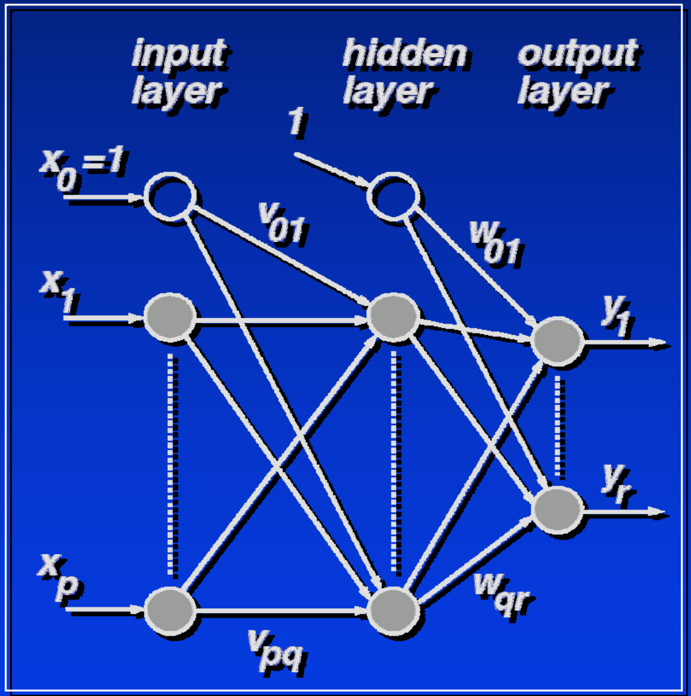
- Backpropagation learning algorithm
  (Rumelhart86) (Bryson69, Werbos74, Parker85)
  - *backpropagation through time*
    (Rumelhart86)

Artificial Neural Networks

Networks of simple computing elements



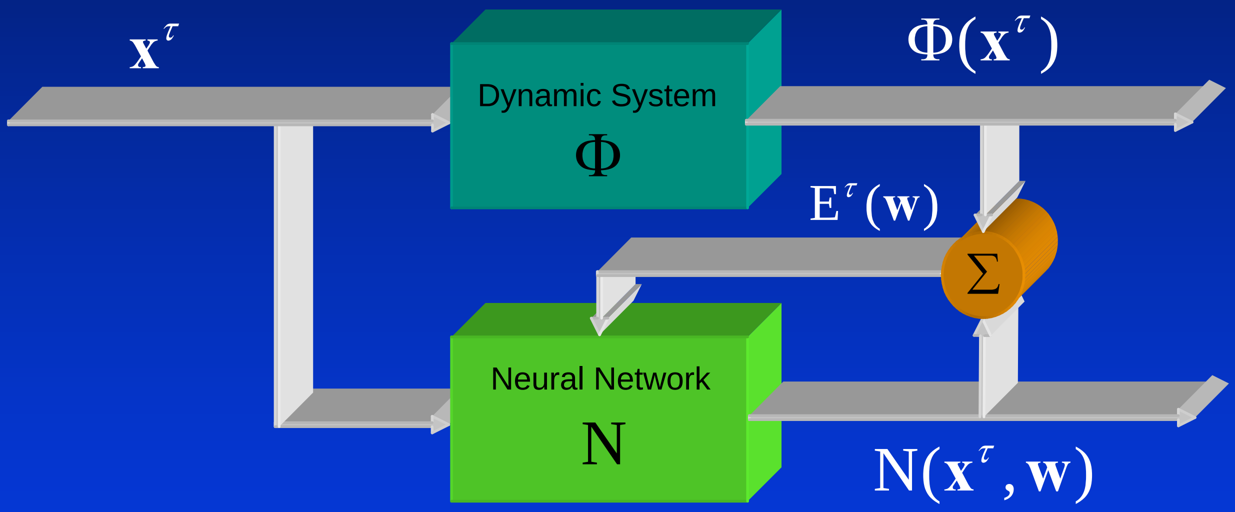
Neuron



Feedforward Network

Backpropagation

Adjusts the weights of a neural network



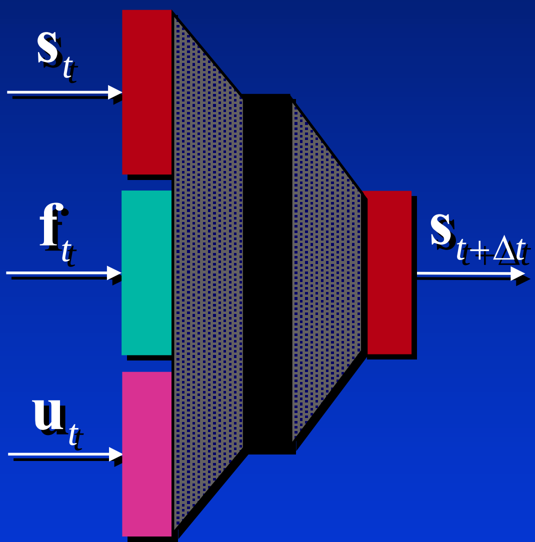
- Approximation error: $$E^{\tau}(\mathbf{w}) = \left\| \Phi(\mathbf{x}^{\tau}) - \mathrm{N}_{\Phi}(\mathbf{x}^{\tau}, \mathbf{w}) \right\|^{2}$$
- Weights update formula: $$\mathbf{w}^{l+1} = \mathbf{w}^{l} - \eta_{w} \nabla_{\mathbf{w}} E^{\tau}(\mathbf{w}^{l})$$

Talk Overview

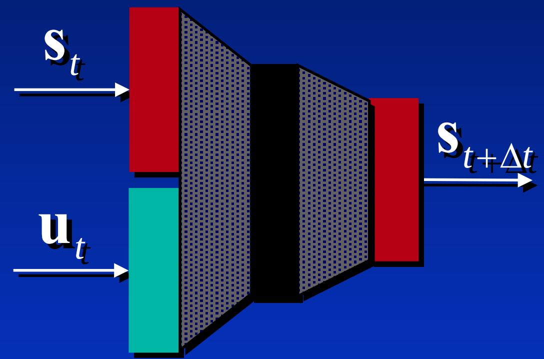
- Introduction
- Artificial neural networks
- From physical models to NeuroAnimators
  – *emulation results*
- NeuroAnimator based controller synthesis
- Conclusion and future work

NeuroAnimator Structure

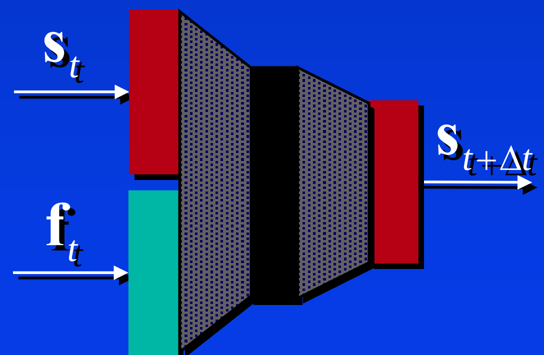
Active dynamic,
nondeterministic forces



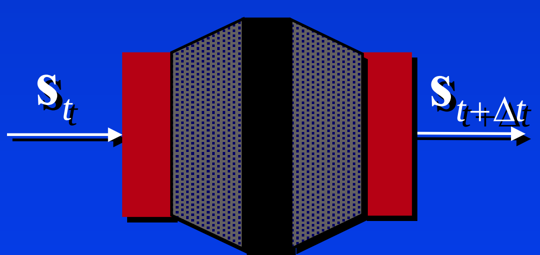
Active dynamic,
deterministic forces



Passive dynamic,
nondeterministic forces



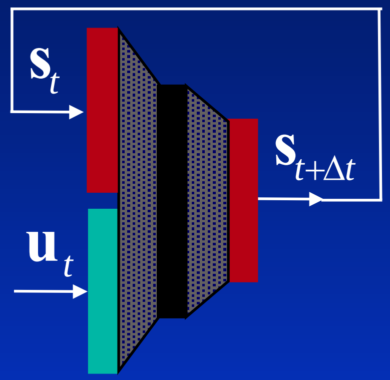
Passive dynamic,
deterministic forces

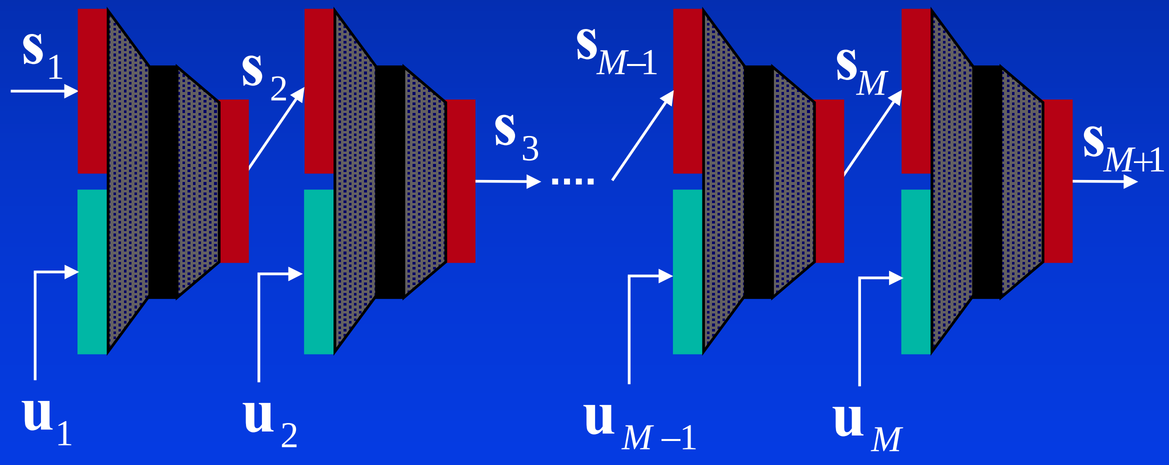


Emulation

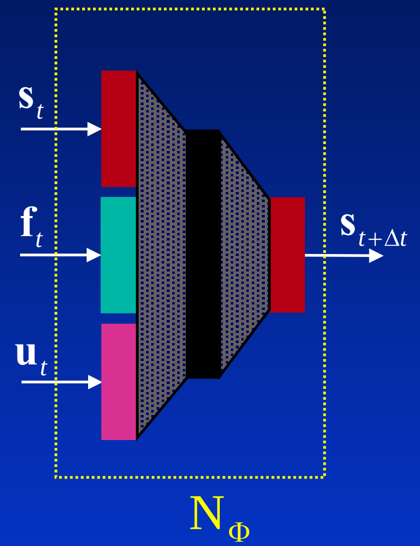
Sequence of network evaluations

$$\mathbf{s}_{t+\Delta t} = \mathrm{N}_{\Phi}(\mathbf{s}_t, \mathbf{u}_t, \mathbf{f}_t)$$

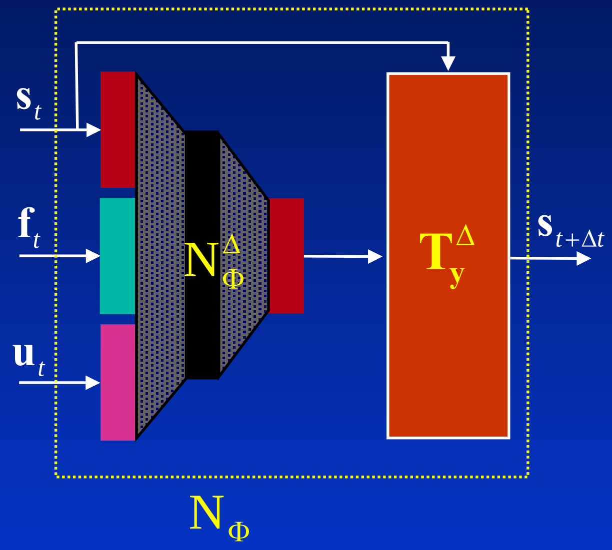




Input & Output Transformations

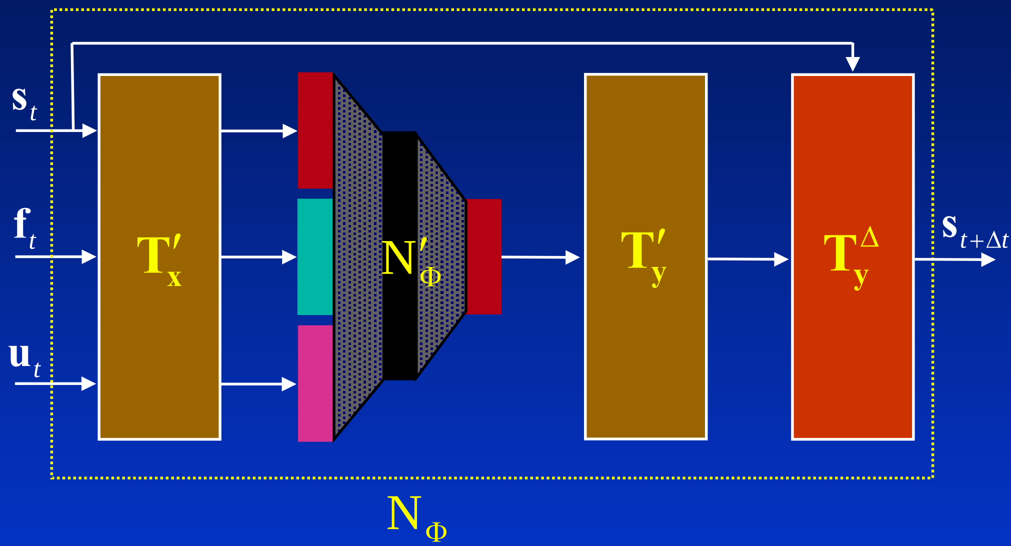


Input & Output Transformations



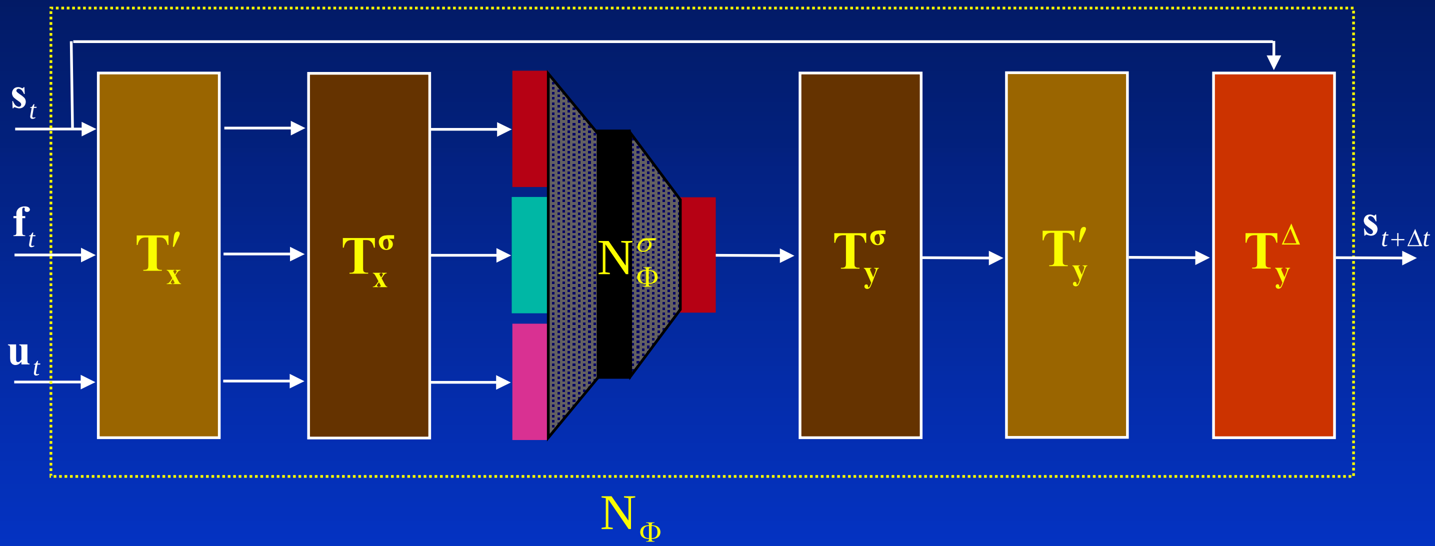
- Predict state changes

Input & Output Transformations



- Predict state changes
- Invariance to translation and rotation

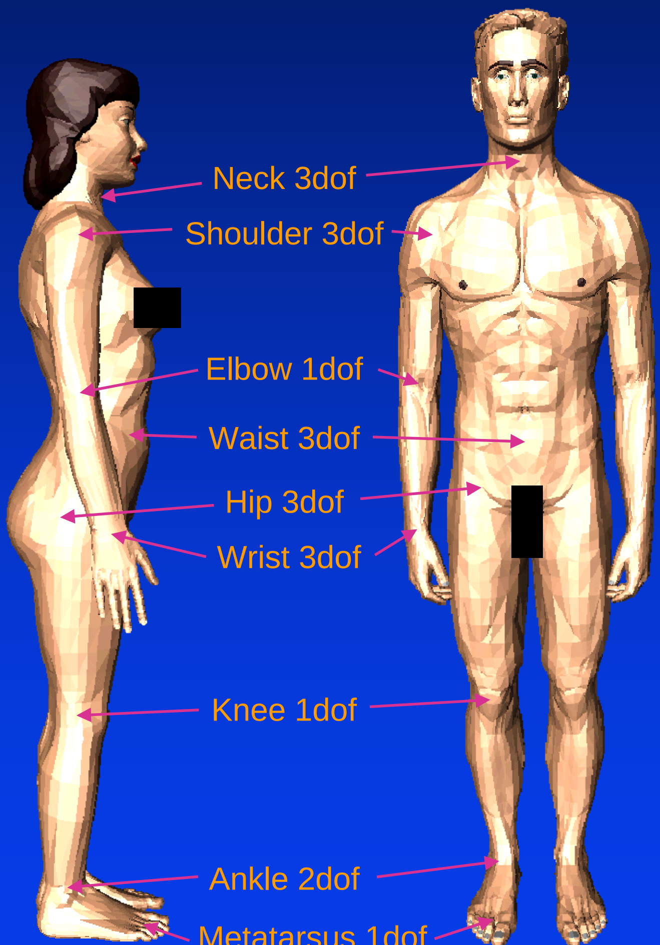
Input & Output Transformations

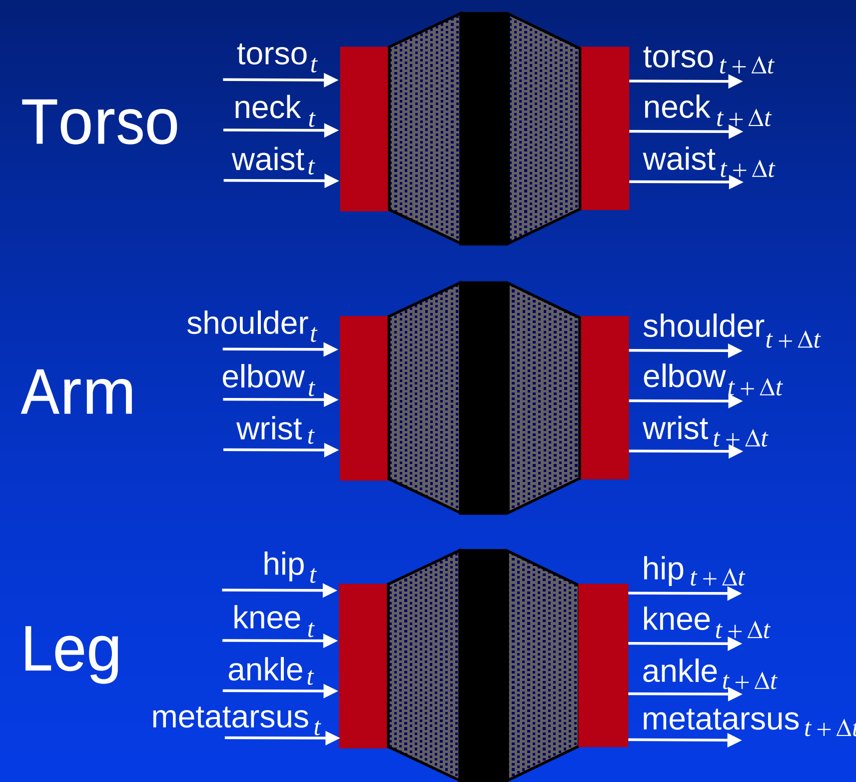


- Predict state changes
- Invariance to translation and rotation
- Normalize inputs and outputs

Hierarchical Emulators

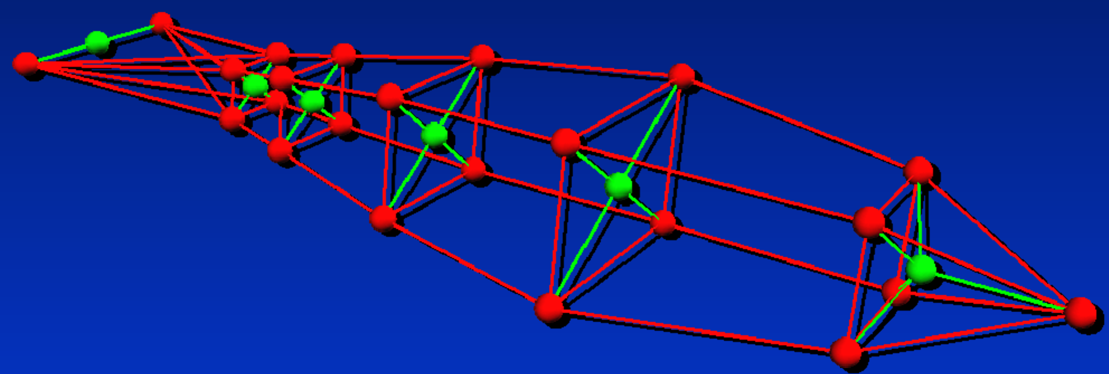
Human model

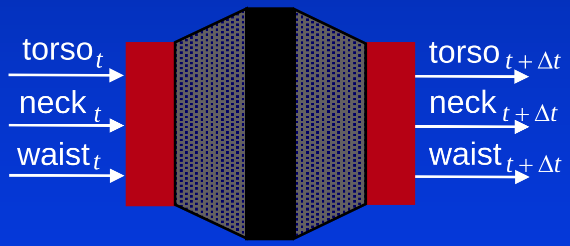


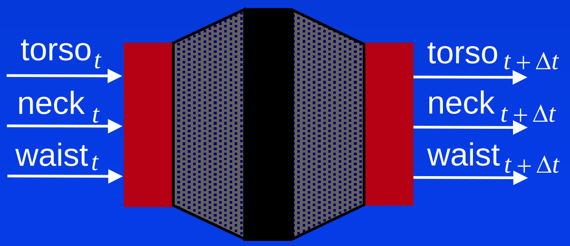


Hierarchical Emulators

Dolphin model





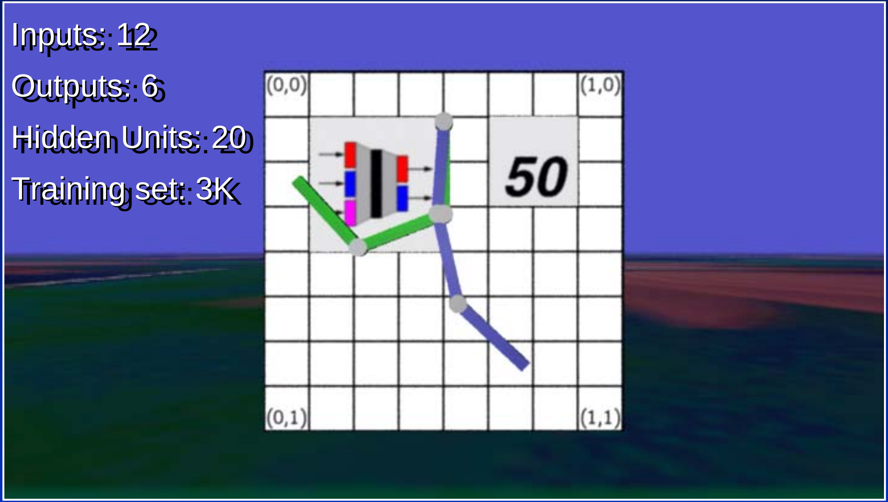


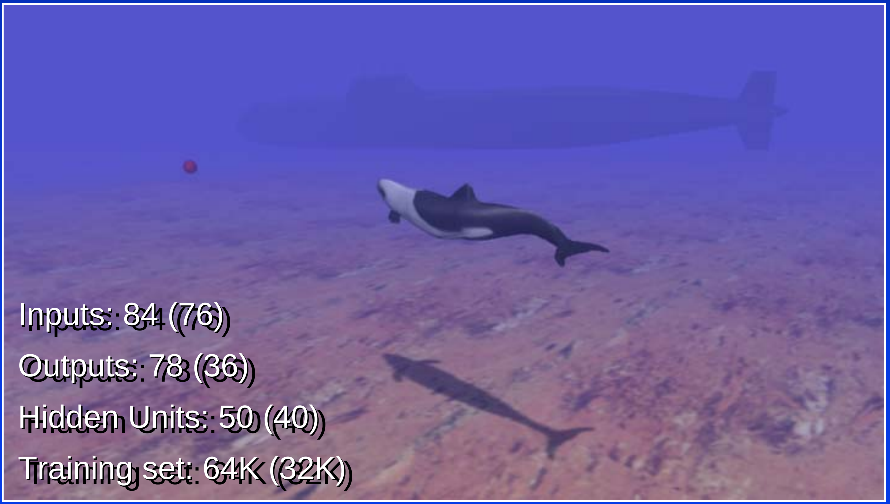
Training NeuroAnimators

Offline backpropagation training of networks

- *"Xerion"* public domain neural network simulator software from the University of Toronto
- Initialize networks with random weights
- Generate training examples with "short-time" physical model simulations from random initial conditions
  - *can reduce training times by sampling state, force, & control inputs that occur most often in practice*

Example NeuroAnimators





Emulation Examples

Emulation Performance

Speedups for a NeuroAnimator with super-timestep Δ t = 50 δ t

• Passive pendulum	94.0x	physical simulation
• Active pendulum	75.3x	”
• Truck	69.7x	”
• Lunar lander	53.7x	”
• Dolphin	66.3x	”

– *approximation error holds ~steady with Δ t*

Talk Overview

- Introduction
- Artificial neural networks
- From physical models to NeuroAnimators
  - *emulation results*
- NeuroAnimator based controller synthesis
  - *control learning results*
- Conclusion and future work

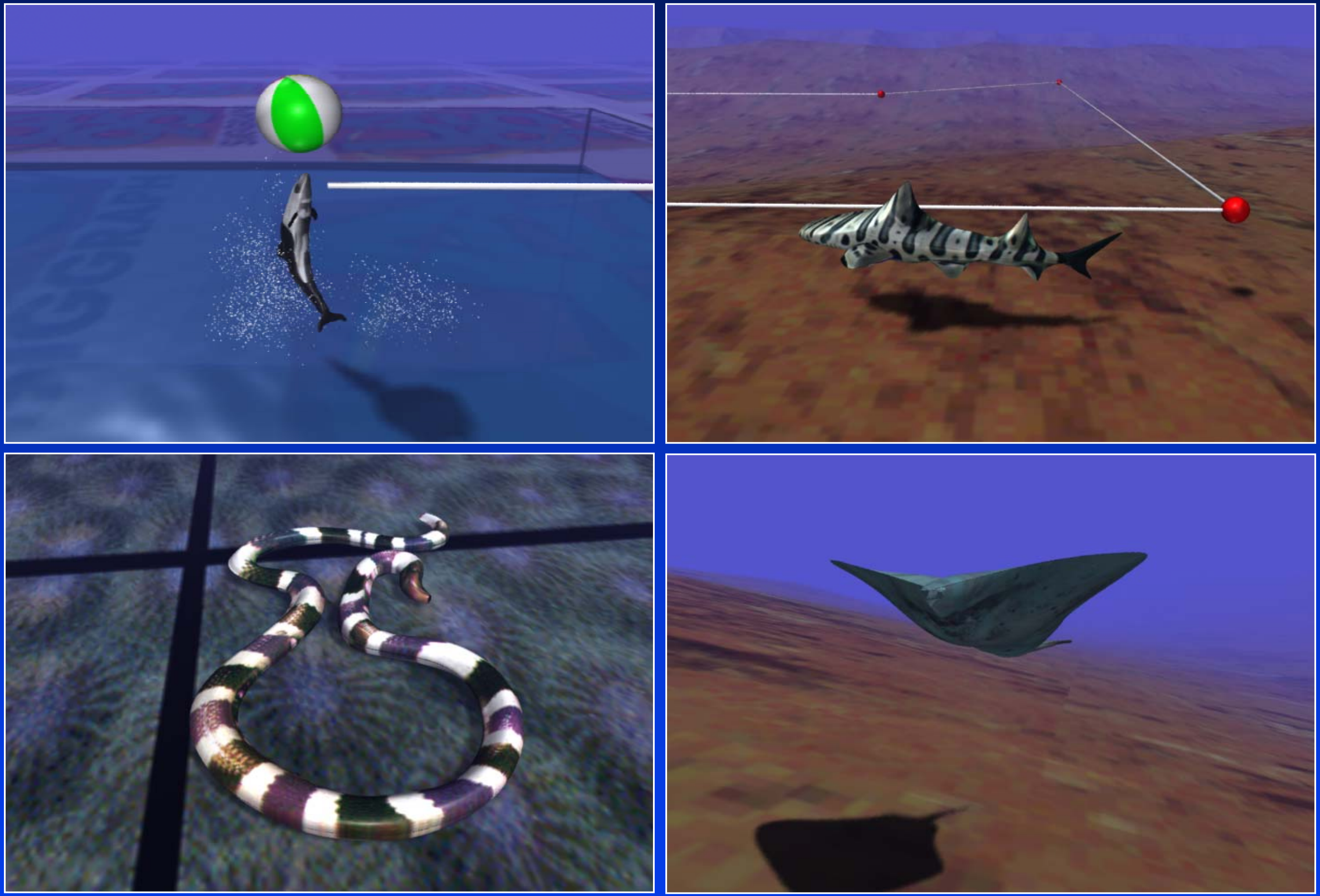
Control of Physical Models

- Inverse dynamics
  (Isaacs87,Barzel88)
- Constraint optimization
  (Brotman88)
- Hand-crafted controllers
  (Miller88, Lee95, Tu94, Wilhelms87, Hodgins95)
- Controller synthesis
  (Goh88, Pandy92, Panne93, Ngo93, Grzeszczuk95)
- Connectionist robotic control
  (Mendel70, Werbos74, Barto87, Jordan88, Nguyen89 - “truck backer-upper”)

Our approach

Controller Synthesis

(Grzeszczuk & Terzopoulos 95)



Controller Synthesis

Optimization of an objective function

- Objective function

Controller quality

Motion quality

$$J(\mathbf{u}) = \mu_u J_u(\mathbf{u}) + \mu_s J_s(\mathbf{s})$$

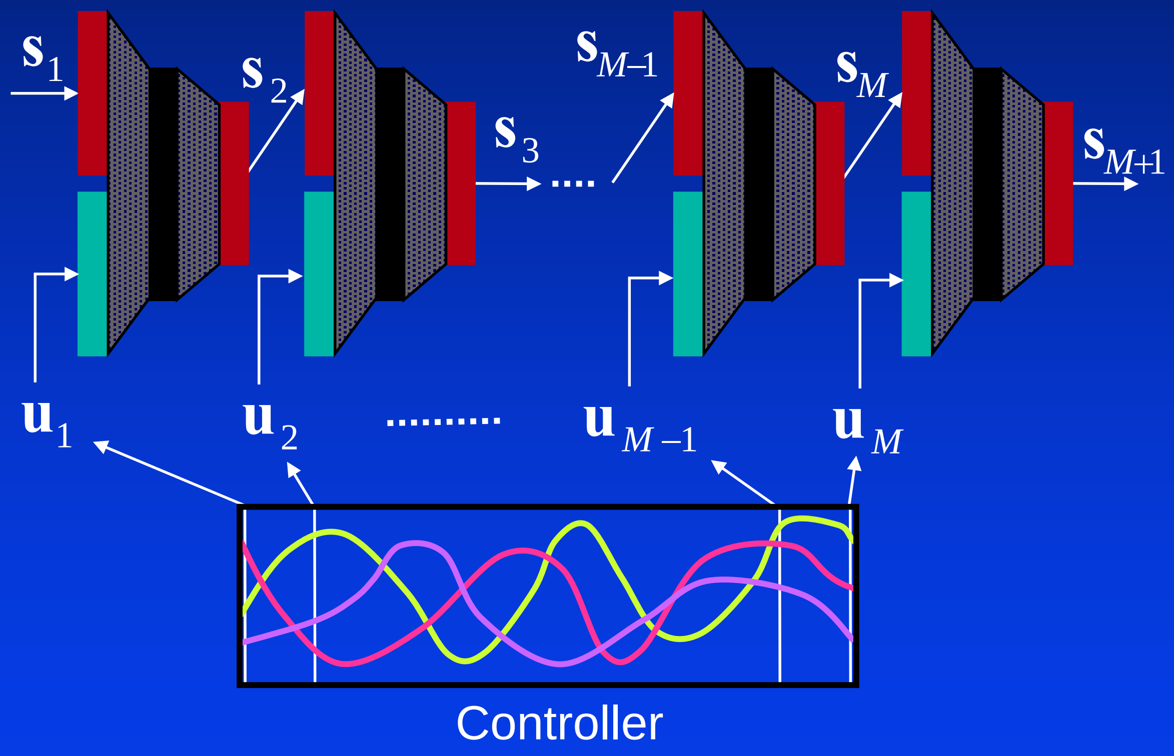
- Controller adjustment rule

$$\mathbf{u}^{l+1} = \mathbf{u}^{l} - \eta_x \nabla_{\mathbf{u}} J(\mathbf{u}^{l})$$

- Trained NeuroAnimator yields gradient analytically
- Controller adjustment consists of two steps...

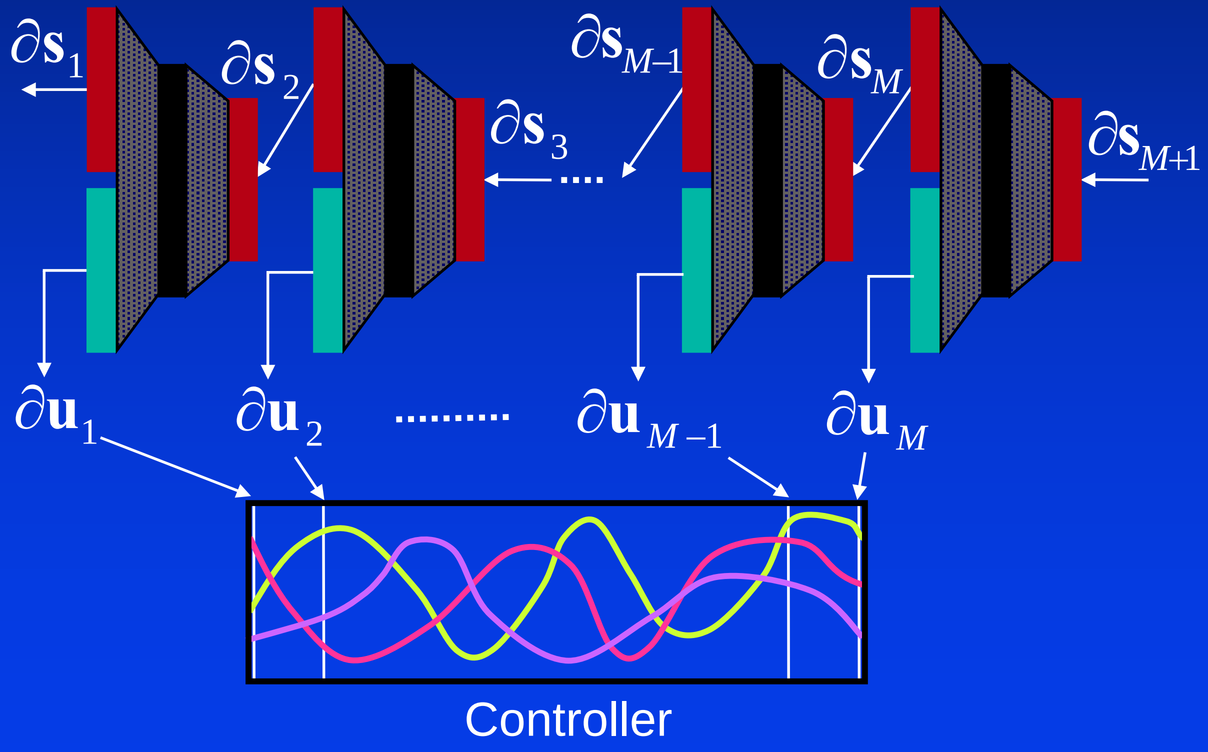
1) Forward Step

Emulates the forward dynamics



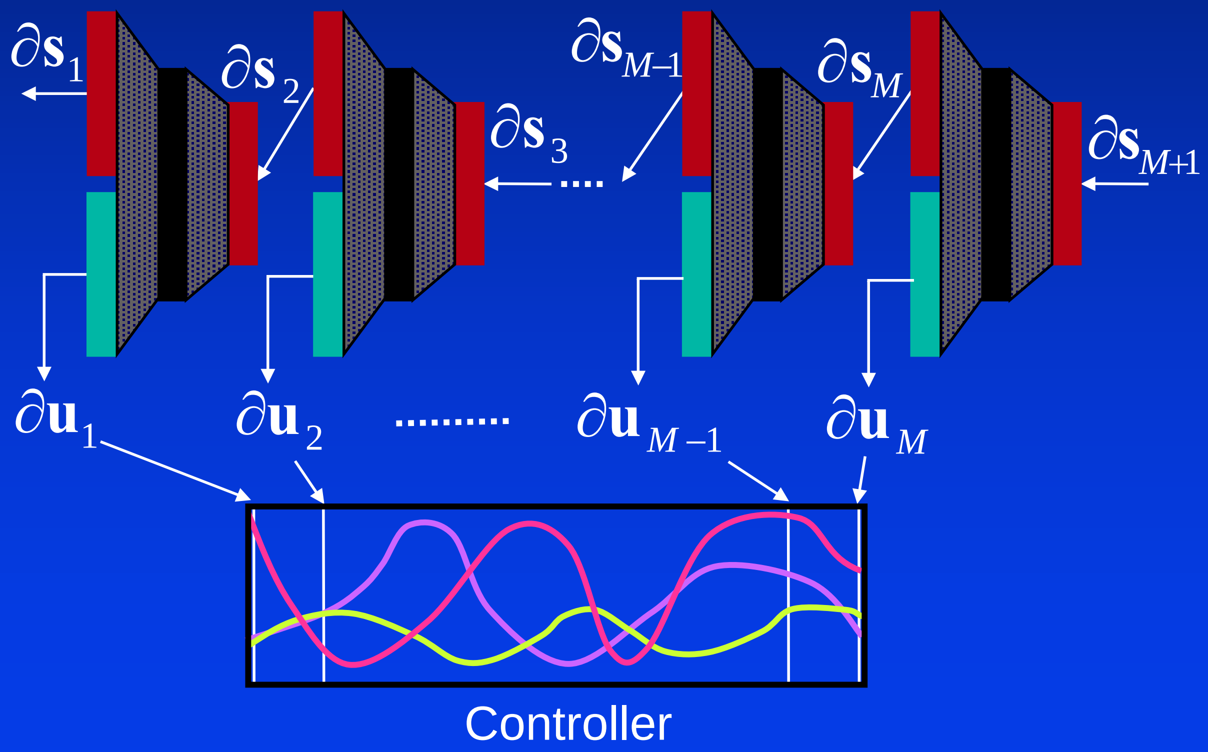
2) Backward Step

Computes gradient using backpropagation through time



2) Backward Step

Computes gradient using backpropagation through time



Control Learning Results

Controller Learning Performance

Talk Overview

- Introduction
- Artificial neural networks
- From physical models to NeuroAnimators
  - *emulation results*
- NeuroAnimator based controller synthesis
  - *control learning results*
- Conclusion and future work

Conclusion

The NeuroAnimator can be a powerful complement to physics-based animation

- NeuroAnimators accurately emulate various physical models up to 2 orders of magnitude faster than numerical simulation
- NeuroAnimator based controller learning algorithm synthesizes motions satisfying prescribed animation goals with up to 2 orders of magnitude fewer iterations

Future Research

- NeuroAnimators for Artificial Life graphical characters
  – *acquiring "mental models" of dynamic worlds*
- NeuroAnimation by motion capture
  – *learning approximations of complex biomechanics*

- Connectionist controller representation
- Hierarchical emulation and control

One More Thing...

“The Eagle has Landed?”

Acknowledgements

Intel Corporation

- Richard Wirt, Fellow & MRL Director
- Edward Langlois
- Steve Hunt
- Sonja Jeter
- Mike Gendimenico
- Michael Shantz, Dave Sprague
- Baining Guo
- John Funge
- Xiaoyuan Tu
- Alexander Reshetov
- Feng Xie
- Bob Liang

University of Toronto

- Zoubin Ghahramani
- Michiel van de Panne
- Mike Revow
- Drew van Camp

Natural Sciences & Engineering Research Council of Canada

Steacie Memorial Fellowship