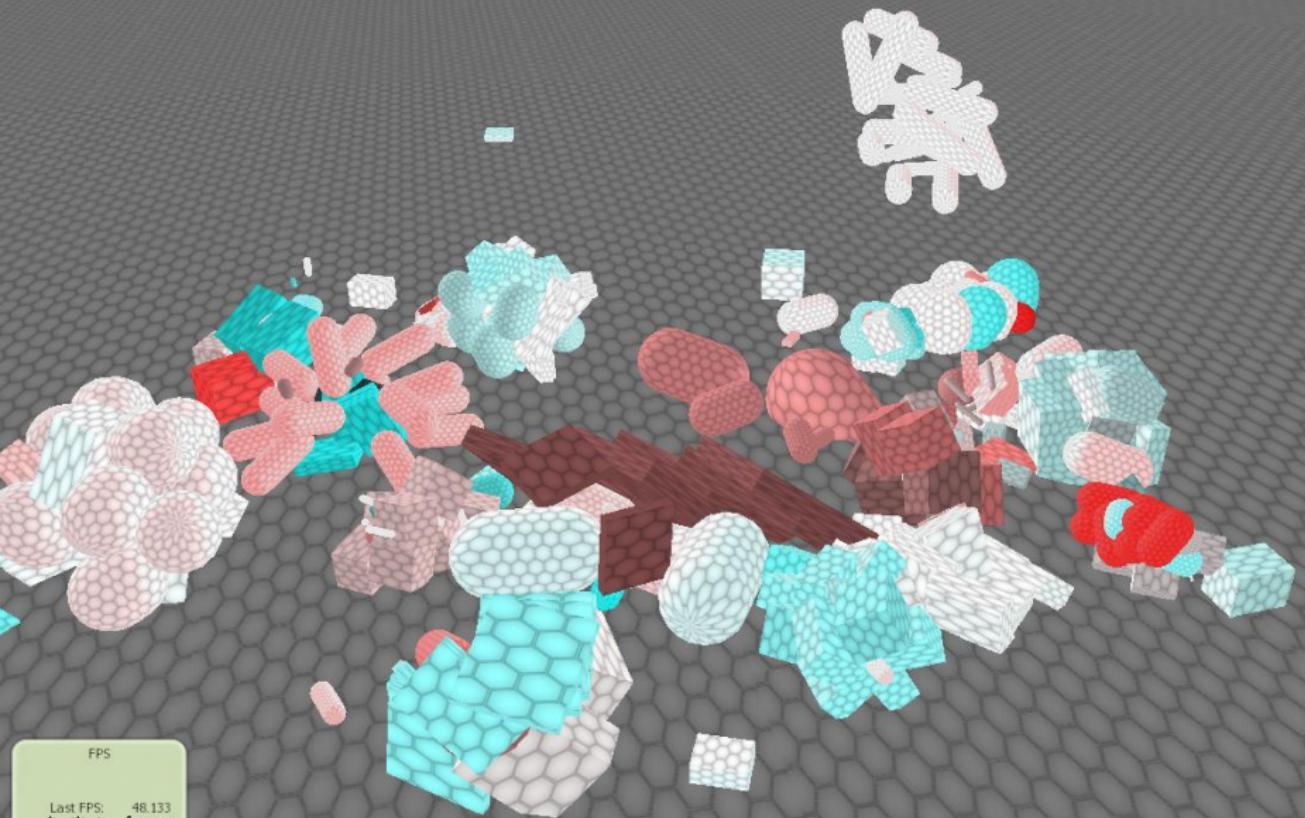




How Evolution might make creatures walk A multistage optimization problem

Benjamin Ellenberger



FPS

Last FPS: 48.133
Institute of 2139C
Neuroinformatics

Benjamin Ellenberger 2015-05-13 2

How does evolution optimize?

The Cycle of Evolution



How does evolution optimize?

- Variation-Selection-Replication cycle

The Cycle of Evolution



How does evolution optimize?

- Variation-Selection-Replication cycle
- Indirect, developmental, messy encoding
(redundant, prone to sudden variation)

The Cycle of Evolution



How does evolution optimize?

- Variation-Selection-Replication cycle
- Indirect, developmental, messy encoding (redundant, prone to sudden variation)
- Embryogenesis/ Genotype (DNA) to Phenotype (Animal body) transcription

The Cycle of Evolution



How does evolution optimize?

- Variation-Selection-Replication cycle
- Indirect, developmental, messy encoding (redundant, prone to sudden variation)
- Embryogenesis/ Genotype (DNA) to Phenotype (Animal body) transcription
- Development of animal after birth (Metamorphosis/ Growth etc.)

The Cycle of Evolution



How does evolution optimize?

- Variation-Selection-Replication cycle
- Indirect, developmental, messy encoding (redundant, prone to sudden variation)
- Embryogenesis/ Genotype (DNA) to Phenotype (Animal body) transcription
- Development of animal after birth (Metamorphosis/ Growth etc.)
- Learn to adapt
- Nature vs. nurture debate

The Cycle of Evolution



Contents

A box of candy

How does evolution optimize?

Can we do similar things?

Evolution

Genetic language

Evolution

Demonstration and Results

Experiments

Oscillator controller

Kuramoto model

Simple limiters theory

Reinforcement Learning and Neural network controller

Evolving Virtual Creatures

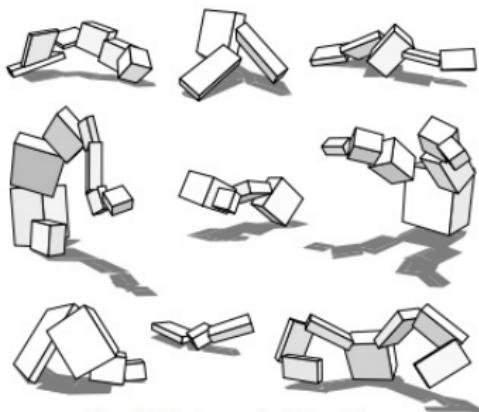


Figure 7: Creatures evolved for walking.

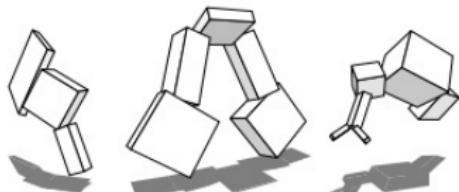


Figure 8: Creatures evolved for jumping.

Evolving Virtual Creatures

- Creatures are built from 3D Primitives and Joints

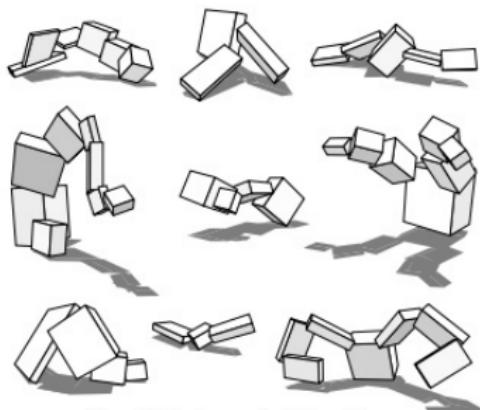


Figure 7: Creatures evolved for walking.

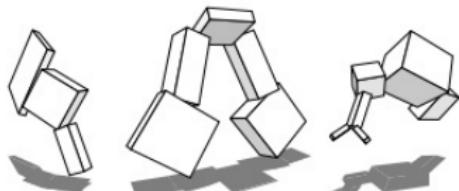


Figure 8: Creatures evolved for jumping.

Evolving Virtual Creatures

- Creatures are built from 3D Primitives and Joints
- Sensors, Controller and Effectors make it move

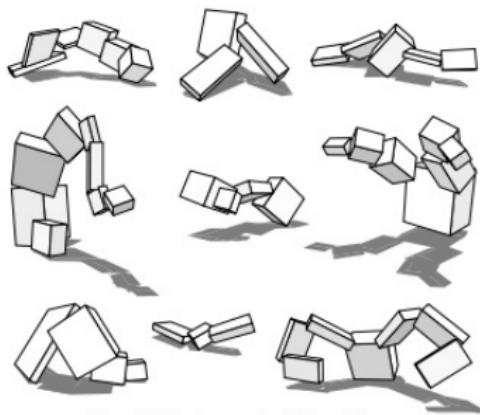


Figure 7: Creatures evolved for walking.

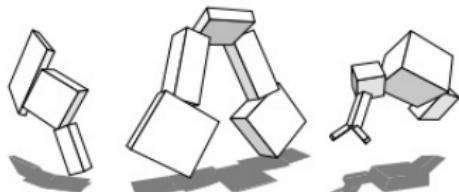


Figure 8: Creatures evolved for jumping.

Evolving Virtual Creatures

- Creatures are built from 3D Primitives and Joints
- Sensors, Controller and Effectors make it move
- Body and controller co-evolved

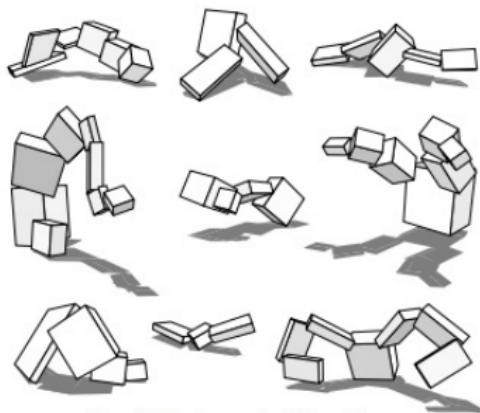


Figure 7: Creatures evolved for walking.

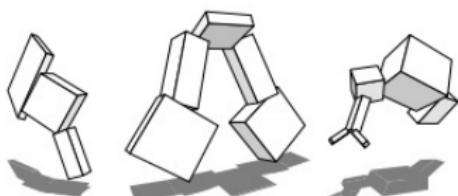
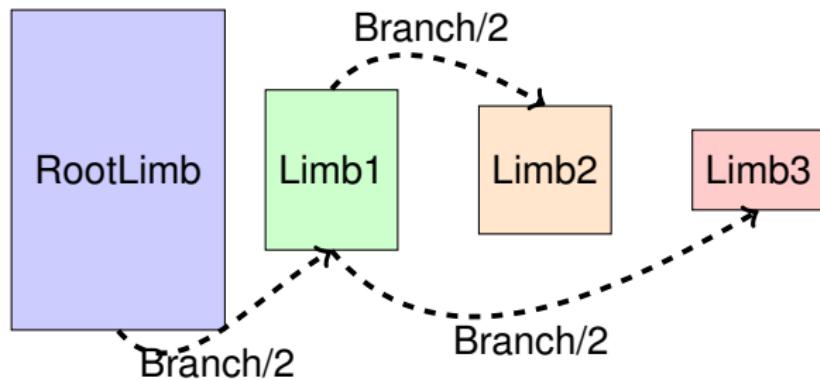


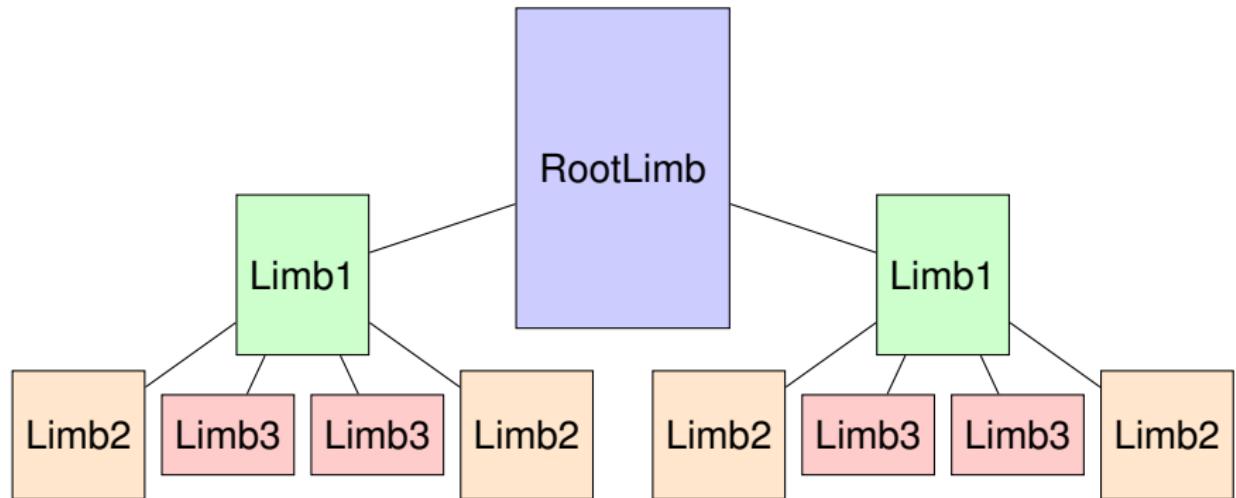
Figure 8: Creatures evolved for jumping.

Genetic language: Genotype

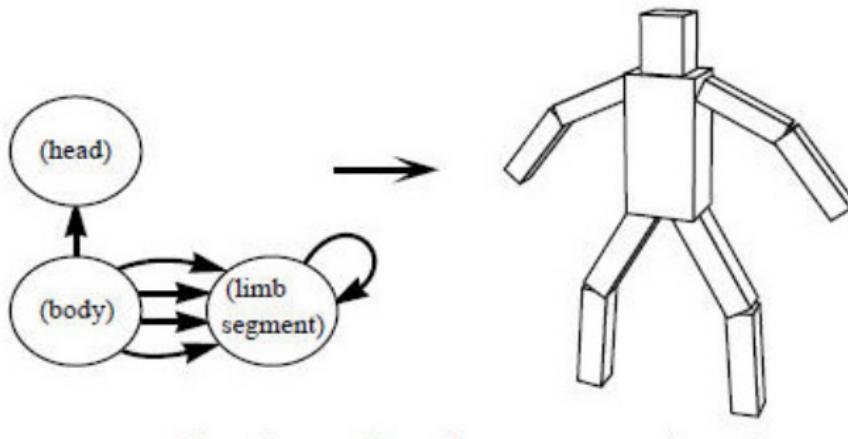


- **Limb** Part of creature body

Genetic language: Phenotype

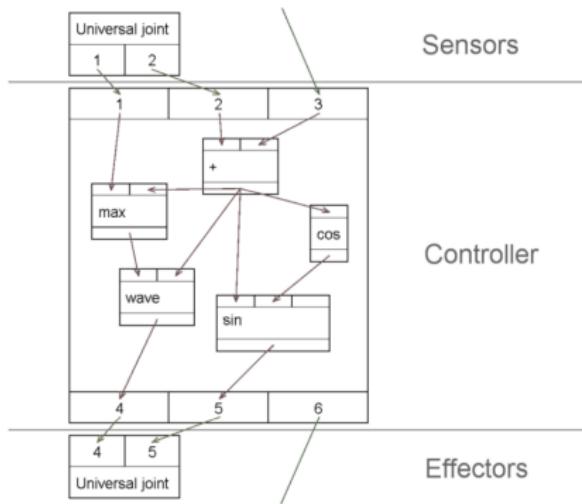
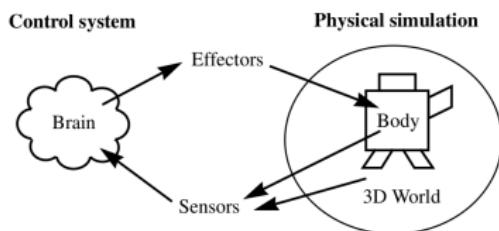


Genetic language: Phenotype cont.



¹Image from Sims K. - Evolving Virtual Creatures (1994)

Execution of creatures



¹Image from Sims K. - Evolving Virtual Creatures (1994)

Evolution

- Selection: Only a certain percentage of creatures are selected for new generation
- Cross-over: Only certain percentage of creatures are allowed to breed
- Mutation
 - Other creatures are subject to mutation
 - Mutation of gene
 - Mutation of gene attributes
 - Mutation of gene branches
- Successful creatures stay in the population and the population is refilled with newly bred and mutated ones

Contents

A box of candy

How does evolution optimize?

Can we do similar things?

Evolution

Genetic language

Evolution

Demonstration and Results

Experiments

Oscillator controller

Kuramoto model

Simple limiters theory

Reinforcement Learning and Neural network controller

Contents

A box of candy

How does evolution optimize?

Can we do similar things?

Evolution

Genetic language

Evolution

Demonstration and Results

Experiments

Oscillator controller

Kuramoto model

Simple limiters theory

Reinforcement Learning and Neural network controller

Oscillator controller

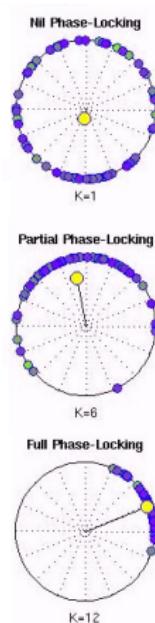
- Sine-wave controller taking frequency, amplitude, X-shift,Y-shift as input which are determined evolutionarily.



Kuramoto model

- A model proposed by Yoshiki Kuramoto¹ to describe synchronization.

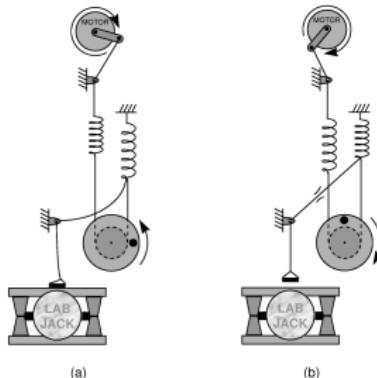
$$\bullet \quad \frac{d\theta_i}{dt} = \omega_i + \frac{K}{N} \sum_{j=1}^N \sin(\theta_j - \theta_i), \quad i = 1 \dots N$$



¹Kuramoto Y. (1984). Chemical Oscillations, Waves, and Turbulence. New York, NY: Springer-Verlag

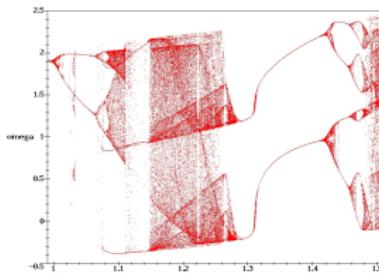
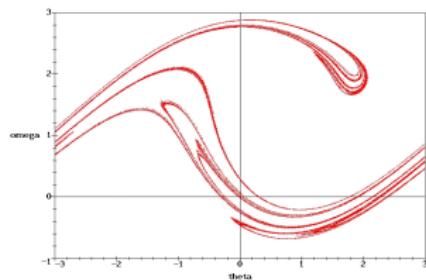
Simplifying control using simple limiters²

- Generally the chaos controller is more complex than the system it controls



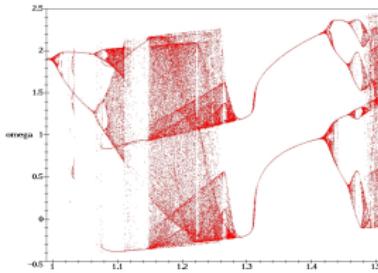
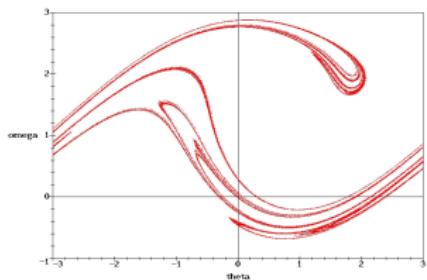
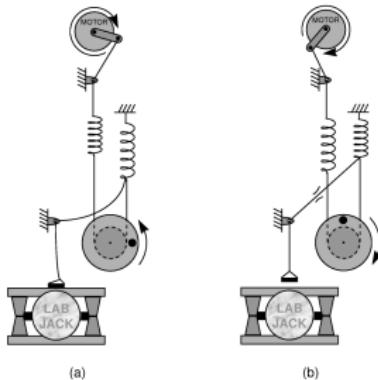
(a)

(b)



Simplifying control using simple limiters²

- Generally the chaos controller is more complex than the system it controls
- Not true for the simple limiter



Simple limiters in nature



Simple limiters in nature

- Muscle length & joint limits



Simple limiters in nature

- Muscle length & joint limits
- The weight of the limbs



Simple limiters in nature

- Muscle length & joint limits
- The weight of the limbs
- The relative position of limbs connected by joints
(Direction of force applied to joints)

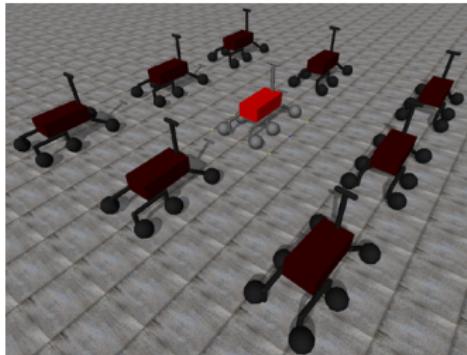
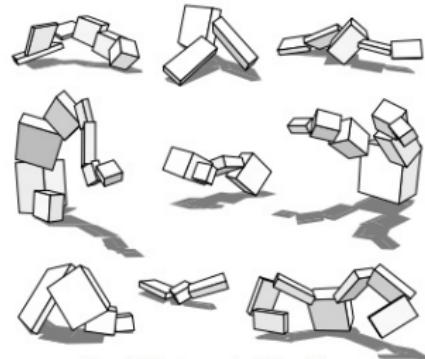


Simple limiters in nature

- Muscle length & joint limits
- The weight of the limbs
- The relative position of limbs connected by joints
(Direction of force applied to joints)
- The fact that physical objects can not interpenetrate each other

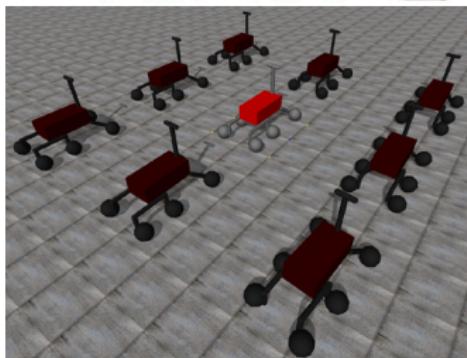
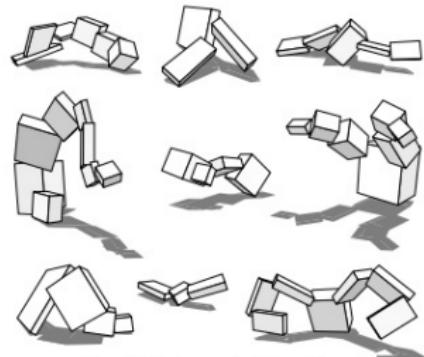


In silico³: Will the simple limiters be used?



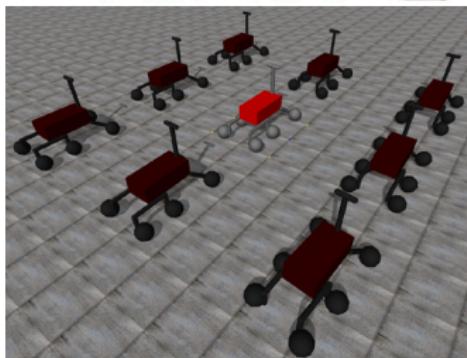
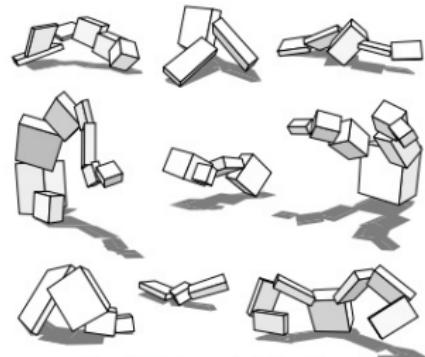
In silico³: Will the simple limiters be used?

- Hypothesis 1: Simple limiters are an omnipresent feature used to reduce the control complexity and to control chaotic movement



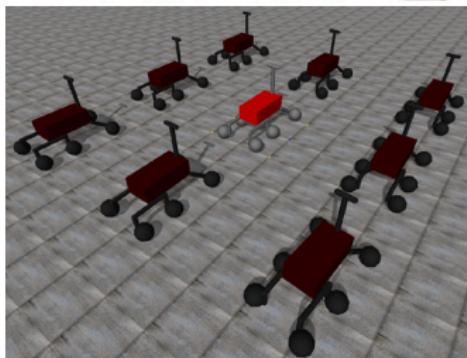
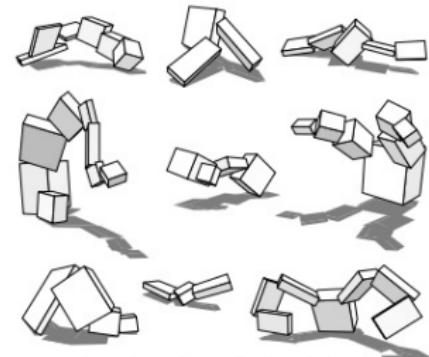
In silico³: Will the simple limiters be used?

- Hypothesis 1: Simple limiters are an omnipresent feature used to reduce the control complexity and to control chaotic movement
- Hypothesis 2: If the world is flat then less simple limiters are used, if the world is dynamic and bumpy then more simple limiters are used.



In silico³: Will the simple limiters be used?

- Hypothesis 1: Simple limiters are an omnipresent feature used to reduce the control complexity and to control chaotic movement
- Hypothesis 2: If the world is flat then less simple limiters are used, if the world is dynamic and bumpy then more simple limiters are used.
- Question remains: Can you live limitless?



Reinforcement Learning and Neural network controller

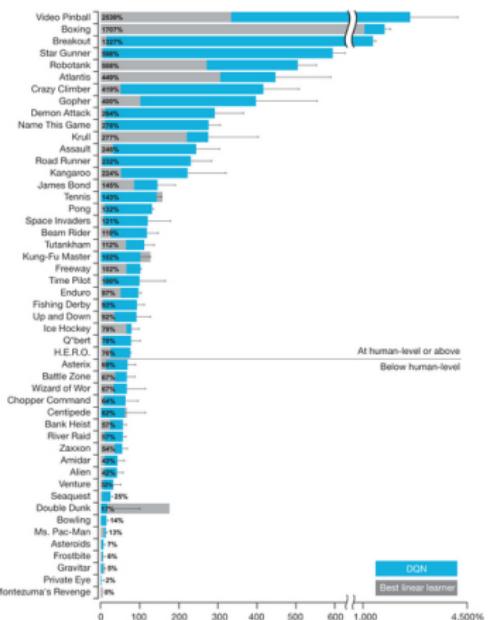
- Reinforcement learning⁴ to make a particular creature learn how to walk
- Actor & Critic Architecture of two Neural Networks



³Sutton, R. & Barto, A. Reinforcement Learning: An Introduction (MIT Press, 1998)

Google Deepmind⁵: Reinforcement Learning on Atari Games

- can learn successful play policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning
- Only for discrete set of actions

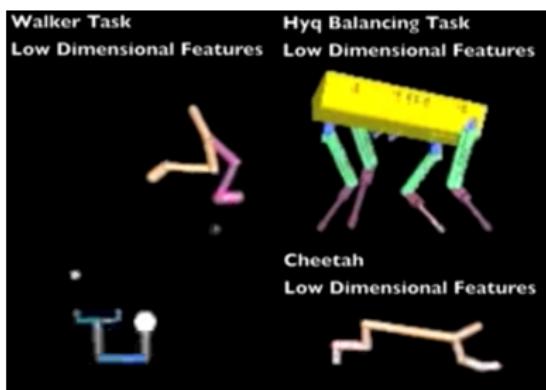


⁴V. Mnih et al., Human-level control through deep reinforcement learning,

Nature 518, 529–533 (26 February 2015)

Google Deepmind⁶: Continuous control with deep reinforcement learning

- can learn successful policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning
- can solve problems such as cartpole swing-up, dexterous manipulation, legged locomotion
- actor-critic algorithm that can operate over continuous action spaces



⁴T.P. Lillicrap et al., Continuous control with deep reinforcement learning,



Discussion!

- Any questions?
- What experiments do you have in mind?
- What else would you change, extend, enhance, improve etc.?
- If you have any ideas later, email me:
`be.ellenberger@gmail.com`
- You can look at my progress:
`https://github.com/benelot/minemonics`

References

- Sims K. - Evolving Virtual Creatures (1994)
- Sims K. - Evolving 3D Morphology and Behavior by Competition (1994)
- Krcah P. - Evolving Virtual Creatures Revisited (2007)
- Corron N. et al. - Controlling Chaos with Simple Limiters (2000)
- Schmidt N. - Bootstrapping perception using information theory: case studies in a quadruped running robot running on different grounds (2013)
- Stoop R. - Theory and Simulation of Neural Networks (2014)