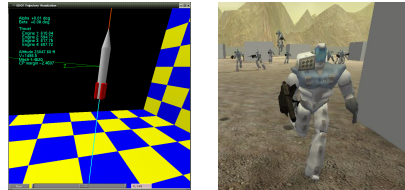


Evolving Neural Networks

Risto Miikkulainen

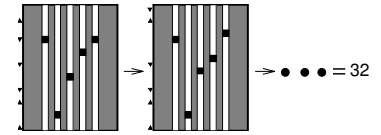
Department of Computer Science
The University of Texas at Austin
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Why Neuroevolution?



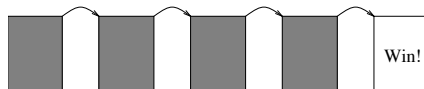
- ▶ Neural nets powerful in many statistical domains
 - ▶ E.g. control, pattern recognition, prediction, decision making
 - ▶ Where no good theory of the domain exists
- ▶ Good supervised training algorithms exist
 - ▶ Learn a nonlinear function that matches the examples
- ▶ What if correct outputs are not known?

Sequential Decision Tasks



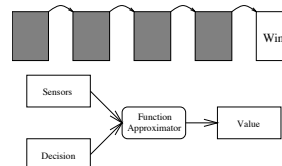
- ▶ POMDP: Sequence of decisions creates a sequence of states
- ▶ No targets: Performance evaluated after several decisions
- ▶ Many important real-world domains:
 - ▶ Robot/vehicle/traffic control
 - ▶ Computer/manufacturing/process optimization
 - ▶ Game playing

Forming Decision Strategies



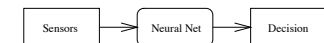
- ▶ Traditionally designed by hand
 - ▶ Too complex: Hard to anticipate all scenarios
 - ▶ Too inflexible: Cannot adapt on-line
- ▶ Need to discover through exploration
 - ▶ Based on sparse reinforcement
 - ▶ Associate actions with outcomes

Standard Reinforcement Learning



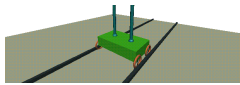
- ▶ AHC, Q-learning, Temporal Differences
 - ▶ Generate targets through prediction errors
 - ▶ Learn when successive predictions differ
- ▶ Predictions represented as a value function
 - ▶ Values of alternatives at each state
- ▶ Difficult with large/continuous state and action spaces
- ▶ Difficult with hidden states

Neuroevolution (NE) Reinforcement Learning



- ▶ NE = constructing neural networks with evolutionary algorithms
- ▶ Direct nonlinear mapping from sensors to actions
- ▶ Large/continuous states and actions easy
 - ▶ Generalization in neural networks
- ▶ Hidden states disambiguated through memory
 - ▶ Recurrency in neural networks⁹⁵

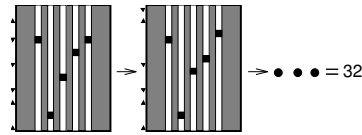
How well does it work?



Poles	Method	Evals	Succ.
One	VAPS	(500,000)	0%
	SARSA	13,562	59%
	Q-MLP	11,331	
	NE	127	
Two	NE	3,416	

- Difficult RL benchmark: Non-Markov Pole Balancing
- NE 3 orders of magnitude faster than standard RL²⁸
- NE can solve harder problems

Role of Neuroevolution

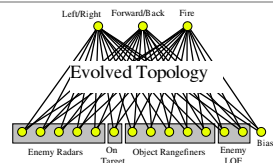


- Powerful method for sequential decision tasks^{16,28,58,111}
 - Optimizing existing tasks
 - Discovering novel solutions
 - Making new applications possible
- Also may be useful in supervised tasks^{53,65}
 - Especially when network topology important
- A unique model of biological adaptation/development^{60,75,106}

Outline

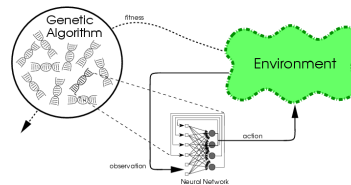
- Basic neuroevolution techniques
- Advanced techniques
 - E.g. combining learning and evolution; novelty search
- Extensions to applications
- Application examples
 - Control, Robotics, Artificial Life, Games

Neuroevolution Decision Strategies



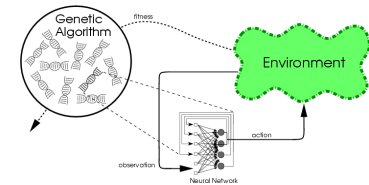
- Input variables describe the state observed through sensors
- Output variables describe actions
- Network between input and output:
 - Nonlinear hidden nodes
 - Weighted connections
- Execution:
 - Numerical activation of input
 - Performs a nonlinear mapping
 - Memory in recurrent connections (POMDP!)

Conventional Neuroevolution (CNE) I



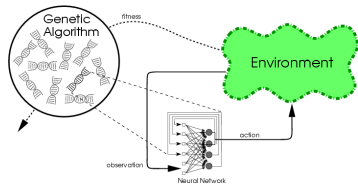
- Evolving connection weights in a population of networks^{53,76,111,112}
- Chromosomes are strings of connection weights (bits or real)
 - E.g. 10010110101100101111001
 - Usually fully connected, fixed topology
 - Initially random

Conventional Neuroevolution II



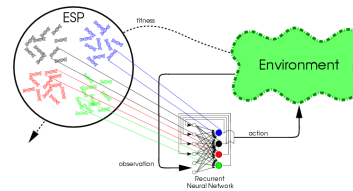
- Parallel search for a solution network
 - Each NN evaluated in the task
 - Good NN reproduce through crossover, mutation
 - Bad thrown away
- Natural mapping between genotype and phenotype
 - GA and NN are a good match!

Problems with CNE



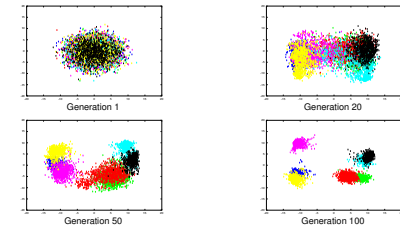
- Evolution converges the population (as usual with EAs)
 - Diversity is lost; progress stagnates
- Competing conventions
 - Different, incompatible encodings for the same solution
- Too many parameters to be optimized simultaneously
 - Thousands of weight values at once

Advanced NE 1: Evolving Partial Networks I



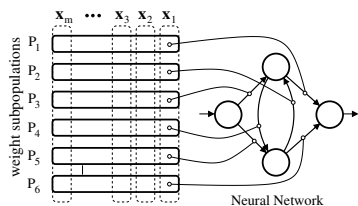
- Evolving individual neurons to cooperate in networks^{1,57,65}
- E.g. Enforced Sub-Populations (ESP²³)
 - Each (hidden) neuron in a separate subpopulation
 - Fully connected; weights of each neuron evolved
 - Populations learn compatible subtasks

Evolving Neurons with ESP



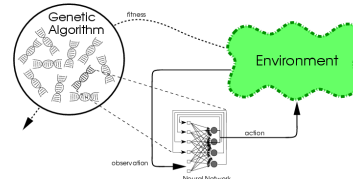
- Evolution encourages diversity automatically
 - Good networks require different kinds of neurons
- Evolution discourages competing conventions
 - Neurons optimized for compatible roles
- Large search space divided into subtasks
 - Optimize compatible neurons

Evolving Partial Networks II



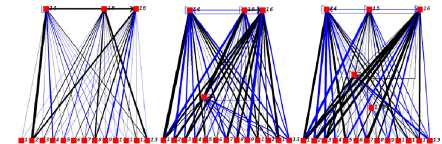
- Extend the idea to evolving connection weights
- E.g. Cooperative Synapse NeuroEvolution (CoSyNE²⁸)
 - Connection weights in separate subpopulations
 - Networks formed by combining neurons with the same index
 - Networks mutated and recombined; indices permuted
- Sustains diversity, results in efficient search

Advanced NE 2: Evolutionary Strategies



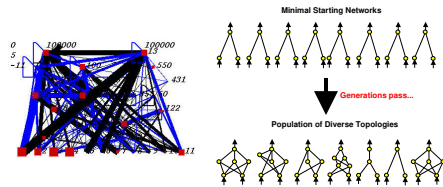
- Evolving complete networks with ES (CMA-ES³⁵)
- Small populations, no crossover
- Instead, intelligent mutations
 - Adapt covariance matrix of mutation distribution
 - Take into account correlations between weights
- Smaller space, less convergence, fewer conventions

Advanced NE 3: Evolving Topologies



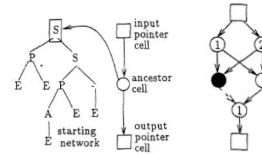
- Optimizing connection weights and network topology^{3,16,21,113}
- E.g. Neuroevolution of Augmenting Topologies (NEAT^{86,89})
- Based on *Complexification*
- Of networks:
 - Mutations to add nodes and connections
- Of behavior:
 - Elaborates on earlier behaviors

Why Complexification?



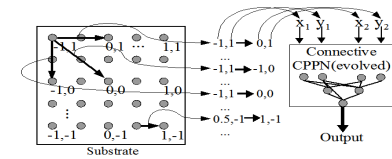
- Problem with NE: Search space is too large
- Complexification keeps the search tractable
 - Start simple, add more sophistication
- Incremental construction of intelligent agents

Advanced NE 4: Indirect Encodings I



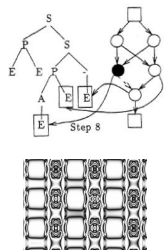
- Instructions for constructing the network evolved
 - Instead of specifying each unit and connection^{3,16,52,83,113}
- E.g. Cellular Encoding (CE³⁰)
- Grammar tree describes construction
 - Sequential and parallel cell division
 - Changing thresholds, weights
 - A "developmental" process that results in a network

Indirect Encodings II



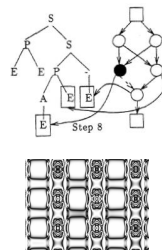
- Encode the networks as spatial patterns
- E.g. Hypercube-based NEAT (HyperNEAT¹²)
- Evolve a neural network (CPPN) to generate spatial patterns
 - 2D CPPN: (x, y) input $\rightarrow$ grayscale output
 - 4D CPPN: (x_1, y_1, x_2, y_2) input $\rightarrow w$ output
 - Connectivity and weights can be evolved indirectly
 - Works with very large networks (millions of connections)

Properties of Indirect Encodings I



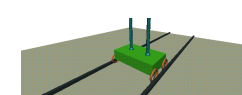
- Smaller search space
- Avoids competing conventions
- Describes classes of networks efficiently
- Modularity, reuse of structures
 - Recurrency symbol in CE: XOR $\rightarrow$ parity
 - Repetition with variation in CPPNs
 - Useful for evolving morphology

Properties of Indirect Encodings II



- Not fully explored (yet)
 - See e.g. GDS track at GECCO
- Promising current work
 - More general L-systems; developmental codings; embryogeny⁹⁰
 - Scaling up spatial coding^{13,22}
 - Genetic Regulatory Networks⁷¹
 - Evolution of symmetries¹⁰³

How Do the NE Methods Compare?



Poles	Method	Evals
Two	CE	(840,000)
	CNE	87,623
	ESP	26,342
	NEAT	6,929
	CMA-ES	6,061
	CoSyNE	3,416

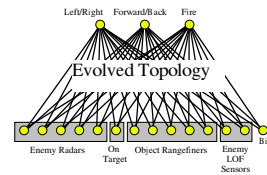
Two poles, no velocities, damping fitness⁹⁴

- Advanced methods better than CNE
- Advanced methods still under development
- Indirect encodings future work

Further NE Techniques

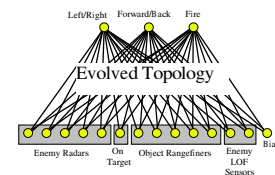
- ▶ Incremental and multiobjective evolution^{25,78,98,112}
- ▶ Utilizing population culture^{5,50,94}
- ▶ Utilizing evaluation history⁴⁷
- ▶ Evolving NN ensembles and modules^{36,46,64,72,108}
- ▶ Evolving transfer functions and learning rules^{8,74,93}
- ▶ Combining learning and evolution
- ▶ Evolving for novelty

Combining Learning and Evolution



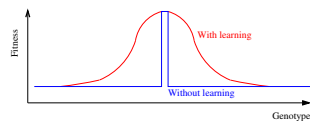
- ▶ Good learning algorithms exist for NN
 - ▶ Why not use them as well?
- ▶ Evolution provides structure and initial weights
- ▶ Fine tune the weights by learning

Lamarckian Evolution



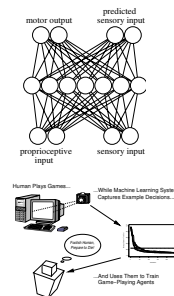
- ▶ Lamarckian evolution is possible^{7,30}
 - ▶ Coding weight changes back to chromosome
- ▶ Difficult to make it work
 - ▶ Diversity reduced; progress stagnates

Baldwin Effect



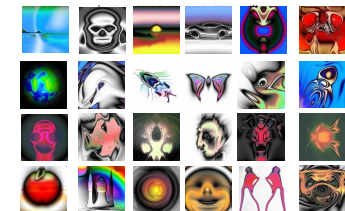
- ▶ Learning can guide Darwinian evolution as well^{4,30,32}
 - ▶ Makes fitness evaluations more accurate
- ▶ With learning, more likely to find the optimum if close
- ▶ Can select between good and bad individuals better
 - ▶ Lamarckian not necessary

Where to Get Learning Targets?



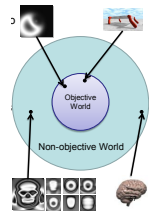
- ▶ From a related task⁶⁰
 - ▶ Useful internal representations
- ▶ Evolve the targets⁵³
 - ▶ Useful training situations
- ▶ From Q-learning equations¹⁰⁹
 - ▶ When evolving a value function
- ▶ Utilize Hebbian learning^{18,87,101}
 - ▶ Correlations of activity
- ▶ From the population^{50,94}
 - ▶ Social learning
- ▶ From humans⁷
 - ▶ E.g. expert players, drivers

Evolving Novelty



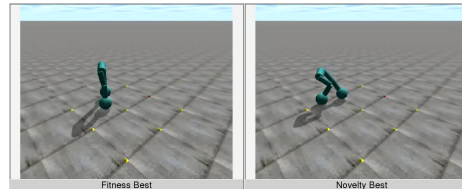
- ▶ Motivated by humans as fitness functions
- ▶ E.g. picbreeder.com, endlessforms.com⁸⁰
 - ▶ CPPNs evolved; Human users select parents
- ▶ No specific goal
 - ▶ Interesting solutions preferred
 - ▶ Similar to biological evolution?

Novelty Search



- Reward maximally different solutions
 - Can be a secondary, diversity objective⁵⁹
 - Or, even as the only objective^{39,41}
- To be different, need to capture structure
 - Problem solving as a side effect
- Potential for innovation
- Needs to be understood better

Novelty Search Demo



- Fitness-based evolution is rigid
 - Requires gradual progress
- Novelty-based evolution is more innovative, natural
 - Allows building on deceptive solutions
- (Demo available at eplex.cs.ucf.edu/noveltysearch)

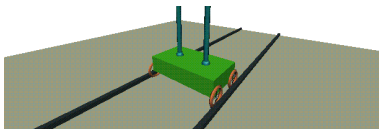
Extending NE to Applications

- Control
- Robotics
- Artificial life
- Gaming

Issues:

- Facilitating robust transfer from simulation^{27,99}
- Utilizing problem symmetry and hierarchy^{38,102,103}
- Utilizing coevolution^{73,91}
- Evolving multimodal behavior^{77,78,108}
- Evolving teams of agents^{6,88,114}
- Making evolution run in real-time⁸⁸

Applications to Control



- Pole-balancing benchmark
 - Originates from the 1960s
 - Original 1-pole version too easy
 - Several extensions: acrobat, jointed, 2-pole, particle chasing⁶⁴
- Good surrogate for other control tasks
 - Vehicles and other physical devices
 - Process control¹⁰⁴

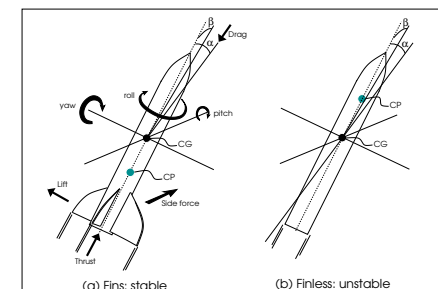
Controlling a Finless Rocket



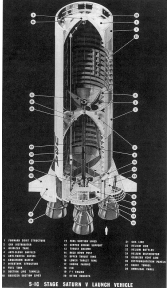
Task: Stabilize a finless version of the Interorbital Systems RSX-2 sounding rocket²⁶

- Scientific measurements in the upper atmosphere
- 4 liquid-fueled engines with variable thrust
- Without fins will fly much higher for same amount of fuel

Rocket Stability

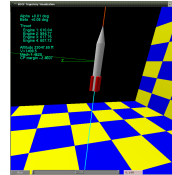


Active Rocket Guidance



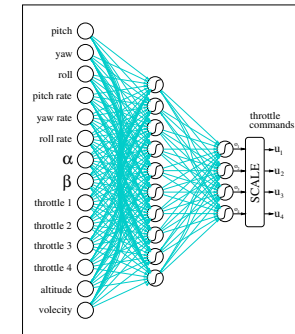
- Used on large scale launch vehicles (Saturn, Titan)
- Typically based on classical linear feedback control
- High level of domain knowledge required
- Expensive, heavy

Simulation Environment: JSBSim

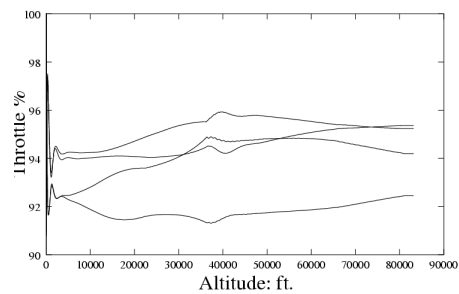


- General rocket simulator
- Models complex interaction between airframe, propulsion, aerodynamics, and atmosphere
- Used by IOS in testing their rocket designs
- Accurate geometric model of the RSX-2

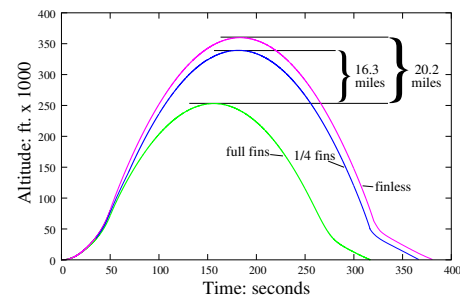
Rocket Guidance Network



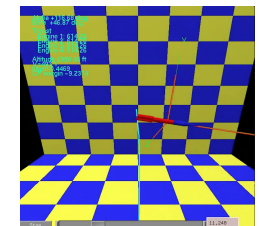
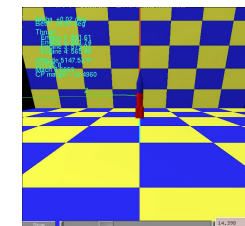
Results: Control Policy



Results: Apogee

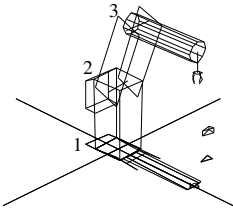


Finless Rocket Control Demo



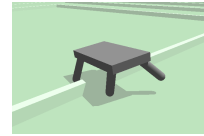
(Demo available at nn.cs.utexas.edu)

Applications to Robotics



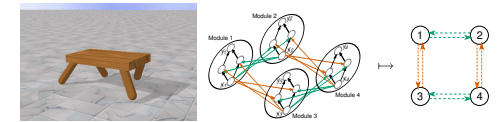
- ▶ Controlling a robot arm⁵⁶
 - ▶ Compensates for an inop motor
- ▶ Robot walking^{34,82,102}
 - ▶ Various physical platforms
- ▶ Mobile robots^{11,17,61,85}
 - ▶ Transfers from simulation to physical robots
 - ▶ Evolution possible on physical robots

Multilegged Walking



- ▶ Navigate rugged terrain better than wheeled robots
- ▶ Controller design is more challenging
 - ▶ Leg coordination, robustness, stability, fault-tolerance, ...
- ▶ Hand-design is generally difficult and brittle
- ▶ Large design space often makes evolution ineffective

ENSO: Symmetry Evolution Approach



- ▶ Symmetry evolution approach^{100,102,103}
 - ▶ A neural network controls each leg
 - ▶ Connections between controllers evolved through symmetry breaking
 - ▶ Connections within individual controllers evolved through neuroevolution

Versatile, Robust Gaits



Different gaits



Obstacle field

- ▶ Different gaits on flat ground
 - ▶ Pronk, pace, bound, trot
 - ▶ Changes gait to get over obstacles
- ▶ (DEMO available at nn.cs.utexas.edu)

Innovative, Effective Solutions



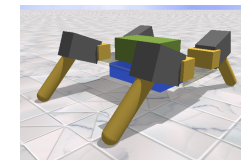
Evolved



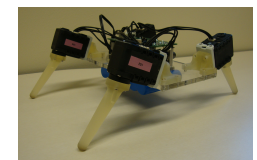
Handcoded

- ▶ Asymmetric gait on inclines
 - ▶ One leg pushes up, others forward
 - ▶ Hard to design by hand
- ▶ (DEMO available at nn.cs.utexas.edu)

Transfer to a Physical Robot I



Simulated



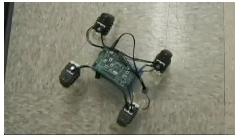
Real

- ▶ Built at Hod Lipson's lab (Cornell U.)
 - ▶ Standard motors, battery, controller board
 - ▶ Custom 3D-printed legs, attachments
 - ▶ Simulation modified to match
- ▶ General, robust transfer⁹⁹
 - ▶ Noise to actuators during simulation
 - ▶ Generalizes to different surfaces, motor speeds
- ▶ (DEMO available at nn.cs.utexas.edu)

Transfer to a Physical Robot II



Evolved



Handcoded

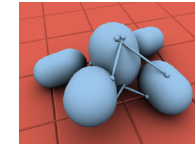
- Evolved a solution for three-legged walking!
- (DEMO available at nn.cs.utexas.edu)

Applications to Artificial Life

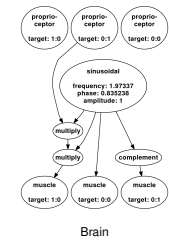


- Gaining insight into neural structure
 - E.g. evolving a command neuron^{2,37,75}
- Understanding animal behaviors
 - Signaling, herding, hunting...^{62,67,69,70,97,106,107,114}

Body-Brain Coevolution

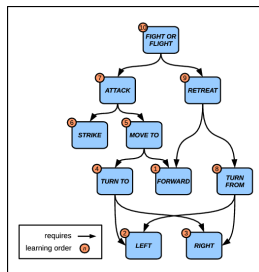


Body



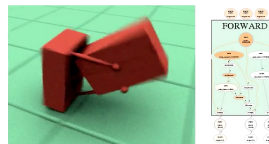
- Evolved Virtual Creatures^{42,43,44,84}
 - Body: Blocks, muscles, joints, sensors (Lessin et al. Alife'14)
 - Brain: A neural network (with general nodes)
 - Evolved together in a physical simulation
- Syllabus, Encapsulation, Pandemonium

Syllabus



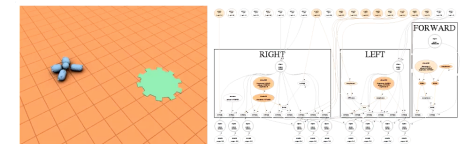
- Constructed by hand; body and brain evolved together

Encapsulation



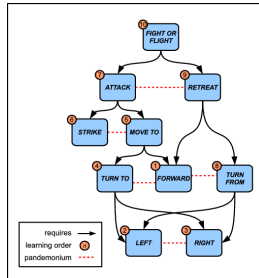
- Once evolved, a trigger node is added

Pandemonium



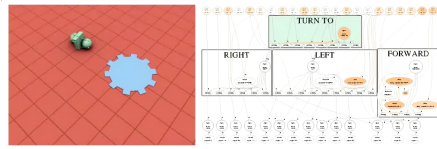
- Conflicting behaviors: Highest trigger wins

Evolving Fight-or-Flight Behavior



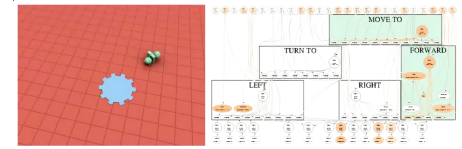
- Step-by-step construction of complex behavior
- Primitives and three levels of complexity
- DEMO (available at nn.cs.utexas.edu)

Turn to Light



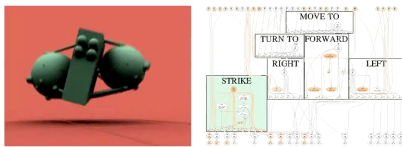
- First level of complexity
- Selecting between alternative primitives

Move to light



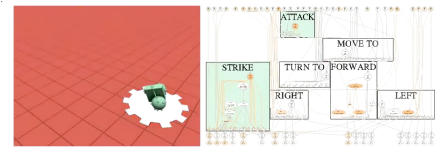
- First level of complexity (Sims 1994)
- Selecting between alternative primitives

Strike



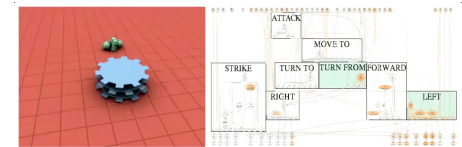
- Alternative behavior primitive

Attack



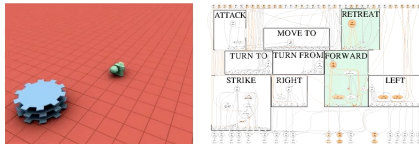
- Second level of complexity (beyond Sims and others)

Turn from Light



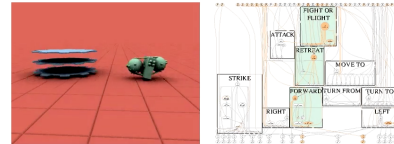
- Alternative first-level behavior

Retreat



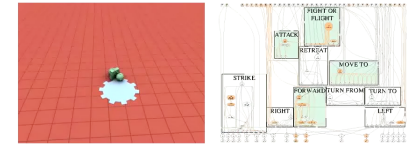
- Alternative second-level behavior

Fight or Flight



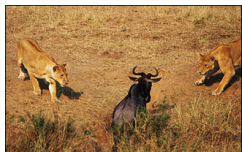
- Third level of complexity

Insight: Body/Brain Coevolution

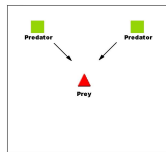


- Evolving body and brain together poses strong constraints
 - Behavior appears believable
 - Worked well also in BotPrize (Turing test for game bots)
- What about constraints from the environment?

Coevolution of Behavior



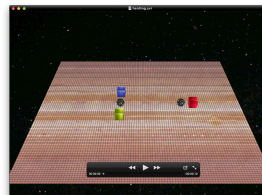
Natural predators and prey



Formalization of behavior

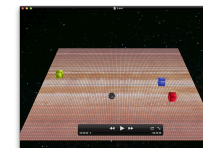
- Complex cooperation observed in pursuit and evasion
 - Motivated by biology, esp. hyenas vs. zebras (Kay Holekamp, MSU)
 - Largely innate, possible to see behaviors and their evolution
- Such behaviors evolve together, in coevolutionary environment
 - Simultaneous competitive and cooperative coevolution^{67,70}

Experimental Setup



- Toroidal grid world
- Predators, prey move with same speed in 4 directions
- No direct communication between team members
 - Communication still possible through stigmergy
- Does a coevolutionary arms race result?
- DEMO (available at nn.cs.utexas.edu)

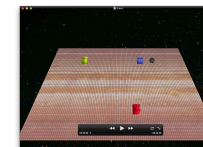
Predator-Prey Arms Race I



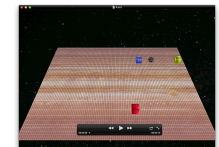
50-75: Single predator catches prey



75-100: Prey evades by circling

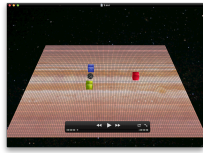


100-150: Two predators cooperate

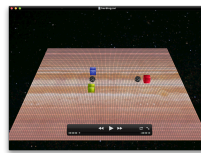


150-180: Prey bails and escapes

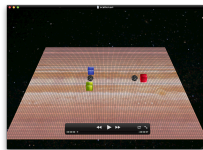
Predator-Prey Arms Race II



180-200: All predators cooperate



200-250: Predators herd two prey

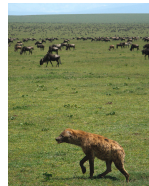


250-300: Prey evade by scattering

Complex behaviors don't evolve in a vacuum

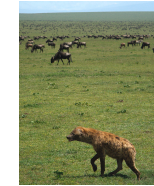
- Result from coevolutionary arms race
- Embedded in a changing environment

Open Questions



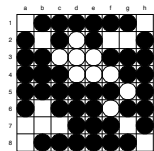
- Role of communication
 - Stigmergy vs. direct communication in hunting¹¹⁴
 - Quorum sensing in e.g. confronting lions
 - Origins of communication⁶⁸ (Rawal et al. Alife'14)
- Role of rankings
 - Efficient selection when evaluation is costly?
- Role of individual vs. team rewards
- Can lead to general computational insights

Bigger Questions



- Gaining insight into cognitive architectures
 - Executive, perception, emotion, memory⁶⁶ (Rajagopalan et al. Alife'14)
- Emergence of language, learning, social structures
- May require overcoming deception
 - Through speciation, niching in nature
 - Through novelty search in computation?⁴⁰

Applications to Games



- Good research platform⁵¹
 - Controlled domains, clear performance, safe
 - Economically important; training games possible
- Board games: beyond limits of search
 - Evaluation functions in checkers, chess^{9,19,20}
 - Filtering information in go, othello^{54,52}
 - Opponent modeling in poker⁴⁸

Discovering Novel Strategies in Othello



(a)



(b)



(c)

- Players take turns placing pieces
- Each move must flank opponent's piece
- Surrounded pieces are flipped
- Player with most pieces wins

Strategies in Othello



(a)



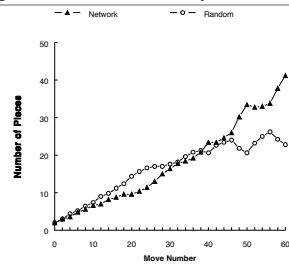
(b)



(c)

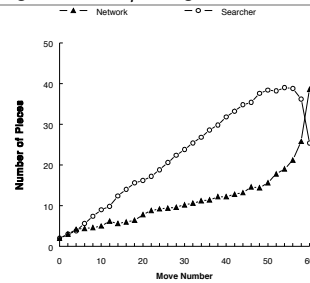
- Positional
 - Number of pieces and their positions
 - Typical novice strategy
- Mobility
 - Number of available moves: force a bad move
 - Much more powerful, but counterintuitive
 - Discovered in 1970's in Japan

Evolving Against a Random Player



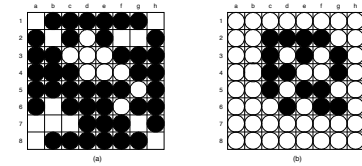
- ▶ Network sees the board, suggests moves by ranking⁵⁵
- ▶ Networks maximize piece counts throughout the game
- ▶ A positional strategy emerges
- ▶ Achieved 97% winning percentage

Evolving Against an α - β Program



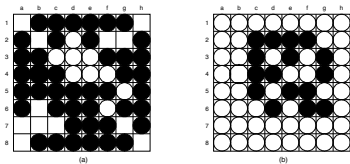
- ▶ Iago's positional strategy destroyed networks at first
- ▶ Evolution turned low piece count into an advantage
- ▶ Mobility strategy emerged!
- ▶ Achieved 70% winning percentage

Example game



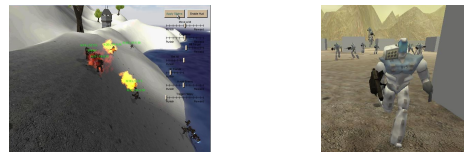
- ▶ Black's positions strong, but mobility weak
- ▶ White (the network) moves to f2
- ▶ Black's available moves b2, g2, and g7 each will surrender a corner
- ▶ The network wins by forcing a bad move

Discovering Novel Strategies



- ▶ Neuroevolution discovered a strategy novel to us
- ▶ "Evolution works by tinkering"
 - ▶ So does neuroevolution
 - ▶ Initial disadvantage turns into novel advantage

Video Games



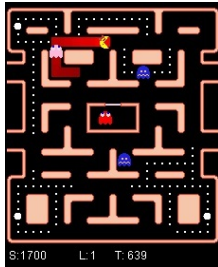
- ▶ Economically and socially important
- ▶ GOFAI does not work well
 - ▶ Embedded, real-time, noisy, multiagent, changing
 - ▶ Adaptation a major component
- ▶ Possibly research catalyst for CI
 - ▶ Like board games were for GOFAI in the 1980s

Video Games II



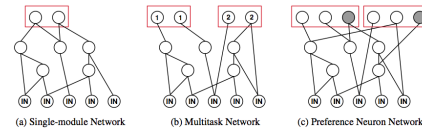
- ▶ Can be used to build "mods" to existing games
 - ▶ Adapting characters, assistants, tools
- ▶ Can also be used to build new games
 - ▶ New genre: Machine Learning game

Challenge 1: Evolving Multimodal Behavior



- Agents perform many different tasks
 - E.g. eat pills, avoid ghosts, eat powerpills, eat ghosts
 - Sometimes clearly separate in time
 - Sometimes multiple tasks at once
- How can we evolve them into a single network?

MM-NEAT: Modular Multiobjective Approach



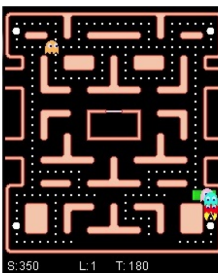
- Evolution discovers modules and when to use them
 - Vs. human-designed division with multitasking
- Multiple modules with preference neurons⁷⁹
 - Modules implement different behaviors
 - Preference neurons used to choose among them
 - Module-mutation adds new modules
- Evolved towards multiple objectives
 - Correspond to dimensions of game play
 - E.g. pills and ghosts in Ms. Pac-Man
- Cf. (Li et al. Allie'14)⁴⁵

Human-Designed Task Division



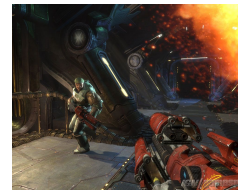
- Multitask approach
 - One module for threat ghosts
 - Another module for edible ghosts
 - Works ok, but...
 - (DEMO available at nn.cs.utexas.edu)

Evolution-Discovered Task Division



- One module used 95% of the time
 - Eat pills, avoid ghosts, chase ghosts
 - Different behaviors with a common base
- A second module 5% of the time
 - Luring ghosts near a power pill
 - Escaping from tight spaces
- A different multimodal perspective
- Not as obvious, but more powerful
- (DEMO available at nn.cs.utexas.edu)

Challenge 2: Evolving Humanlike Behavior



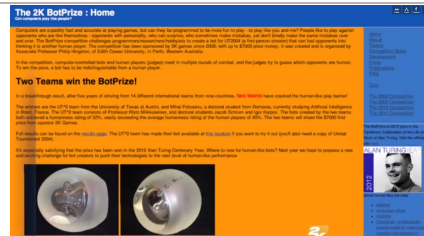
- Botprize competition, 2007-2012
 - Turing Test for game bots (\$10,000 prize)
- Three players in Unreal Tournament 2004:
 - Human confederate: tries to win
 - Software bot: pretends to be human
 - Human judge: tries to tell them apart!

Evolving an Unreal Bot



- Evolve effective fighting behavior
 - Human-like with resource limitations (speed, accuracy...)
- Also scripts & learning from humans (unstuck, wandering...)
- 2007-2011: bots 25-30% vs. humans 35-80% human
- 6/2012 best bot better than 50% of the humans
- 9/2012...?

Success!!!



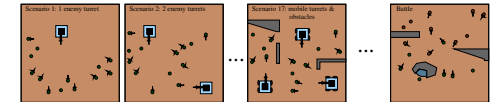
- ▶ In 2012, two teams reach the 50% mark!
- ▶ Fascinating challenges remain:
 - ▶ Judges can still differentiate in seconds
 - ▶ Judges lay cognitive, high-level traps
 - ▶ Team competition: collaboration as well
- ▶ (DEMO available at nn.cs.utexas.edu)

A New Genre: Machine Learning Games



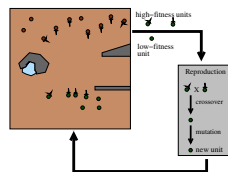
- ▶ E.g. NERO
 - ▶ Goal: to show that machine learning games are viable
 - ▶ Professionally produced by *Digital Media Collaboratory*, UTAustin
 - ▶ Developed mostly by volunteer undergraduates

NERO Gameplay



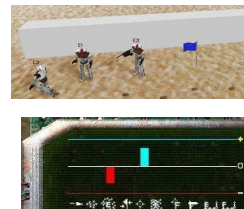
- ▶ Teams of agents trained to battle each other
 - ▶ Player trains agents through exercises
 - ▶ Agents evolve in real time
 - ▶ Agents and player collaborate in battle
- ▶ New genre: *Learning is the game*^{31,88}
 - ▶ Challenging platform for reinforcement learning
 - ▶ Real time, open ended, requires discovery
- ▶ Try it out:
 - ▶ Available for download at <http://nerogame.org>
 - ▶ Open source research platform version at opennero.googlecode.com

Real-time NEAT



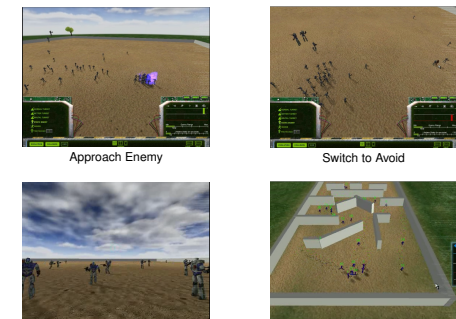
- ▶ A parallel, continuous version of NEAT⁸⁸
- ▶ Individuals created and replaced every n ticks
- ▶ Parents selected probabilistically, weighted by fitness
- ▶ Long-term evolution equivalent to generational NEAT

NERO Player Actions



- ▶ Player can place items on the field
 - e.g. static enemies, turrets, walls, rovers, flags
- ▶ Sliders specify relative importance of goals
 - e.g. approach/avoid enemy, cluster/disperse, hit target, avoid fire...
- ▶ Networks evolved to control the agents

NERO Training Demo



(DEMO available at nn.cs.utexas.edu)

NERO Battle Demo



Aggressive vs. Avoidant



Teams of three

(DEMO available at nn.cs.utexas.edu)

Numerous Other Applications

- ▶ Creating art, music, dance...^{10,15,33,81}
- ▶ Theorem proving¹⁴
- ▶ Time-series prediction⁴⁹
- ▶ Computer system optimization²⁴
- ▶ Manufacturing optimization²⁹
- ▶ Process control optimization^{104,105}
- ▶ Measuring top quark mass¹¹⁰
- ▶ Etc.

Evaluation of Applications



- ▶ Neuroevolution strengths
 - ▶ Can work very fast, even in real-time
 - ▶ Potential for arms race, discovery
 - ▶ Effective in continuous, non-Markov domains
- ▶ Requires many evaluations
 - ▶ Requires an interactive domain for feedback
 - ▶ Best when parallel evaluations possible
 - ▶ Works with a simulator & transfer to domain

Conclusion

- ▶ NE is a powerful technology for sequential decision tasks
 - ▶ Evolutionary computation and neural nets are a good match
 - ▶ Lends itself to many extensions
 - ▶ Powerful in applications
- ▶ Easy to adapt to applications
 - ▶ Control, robotics, optimization
 - ▶ Artificial life, biology
 - ▶ Gaming: entertainment, training
- ▶ Lots of future work opportunities
 - ▶ Theory needs to be developed
 - ▶ Indirect encodings
 - ▶ Learning and evolution
 - ▶ Knowledge, interaction, novelty

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