

Neuroevolution of Combat Bots



Artificial Intelligence for
Interactive Media and Games

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CS/IMGD 4100 (B 14)1

- Constructing Complex NPC Behavior via Multi-Objective Neuroevolution
AIIDE, Stanford, CA, Oct. 2008

- Jacob Schrum
- Risto Miikkulainen




- University of Texas at Austin, CS Dept.

<http://www.cs.utexas.edu/~schrum2/>

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Outline

- Machine Learning
- Neural Nets
- Genetic Algorithms
- Neuroevolution of Combat Bots

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Machine Learning

- algorithms for improving performance based on experience
- why useful for games?
 - avoids “manual” programming labor
 - adapts to changing environment

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Machine Learning

- algorithms for improving *performance* based on experience

“outputs of the system”

- recognizing speech
- diagnosing diseases
- controlling a combat bot

Machine Learning

- algorithms for improving performance based on *experience*

“input data”

(output: recognizing speech)

- sound waves
(output: diagnosing diseases)
- medical symptoms and test results
(output: controlling a combat bot)
- actions of bot and player in game

Machine Learning

- algorithms for *improving* performance based on experience

“measure of performance”

(output: recognizing speech)

- what the person actually said

(output: diagnosing disease)

- disease the patient actually has

(output: controlling a combat bot)

- related to game design
 - how much damage bot inflicts on player
 - how much damage bot receives
 - how much fun the player has (harder to evaluate)

Machine Learning

- algorithms* for improving performance based on experience

“it’s all search (in very large spaces)”

- reinforcement
- Bayesian
- simulated evolution (genetic algorithms)
- etc., etc.
- issues*: efficiency, convergence, etc., etc.

Machine Learning

- *algorithms* for improving performance based on experience

"it's all function approximation"

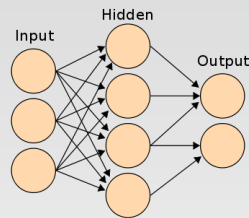
- given input/output pairs ("training set")
 - each with evaluation of good the performance is
 - may be mix of good and bad performances
- induce a function which will produce good output for any input ("test set")

Machine Learning

- supervised vs. unsupervised
 - *supervised*: system is given (by "teacher") a planned sequence of experiences (training set), which will lead to efficient learning
 - *unsupervised*: system generates experiences by itself, e.g., by interacting with environment

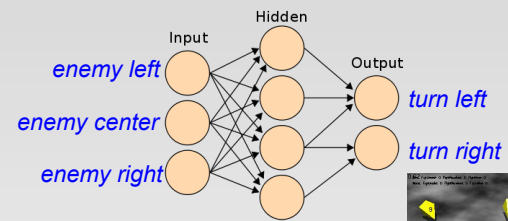
Neural Nets

an interconnected network of nodes, inspired by the network of neurons in the brain

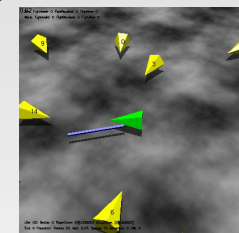


<http://www.ai-junkie.com/ann/evolved/nnt1.html>

Neural Net to Control Combat Bot



(NB: cannot sense other bots)



Neural Net Weights

$$a = x_1 w_1 + x_2 w_2 + x_3 w_3 + \dots + x_n w_n$$

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Neural Nets

- The “knowledge” is in the *structure* of the node connections and the *weights*

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Neural Net Learning

- Initialize all weights to random numbers
- Typical supervised learning
 - start with totally connected network of given depth (hidden layers)
 - apply positive (negative) input/output training pairs
 - iteratively improve weights by *backpropagation* algorithm
- Neuroevolution
 - mutate weights and connections
 - use *genetic algorithm* for selection

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Genetic Algorithms

inspired by natural evolution

- Given:**
 - a genetic representation each solution, e.g.,
 - DNA sequence
 - array of bits
 - neural net
 - a fitness function
 - applied to a genetic representation
 - relative to an “environment” (problem)
 - typically a numerical “score” (higher is better)

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Genetic Algorithms

1. Choose initial population at random
2. Evaluate the fitness of each individual in the population
3. Repeat until termination: (time limit or sufficient fitness achieved)
 1. Select best-ranking individuals to reproduce
 2. Breed new generation through crossover and/or mutation (genetic operations on representation) and give birth to offspring
 3. Evaluate the individual fitness of each offspring
 4. Replace worst ranked part of population with offspring

Neuroevolution of Combat Bots

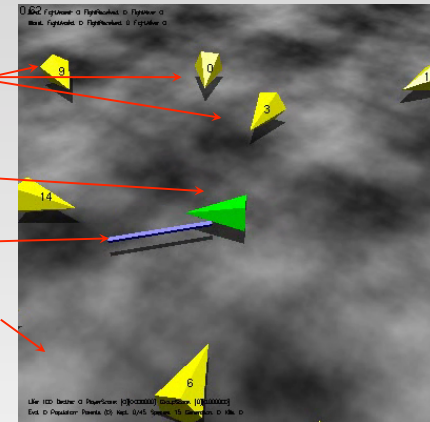
15 bots
(population)
attack player

Player

Bat

Infinite Plane

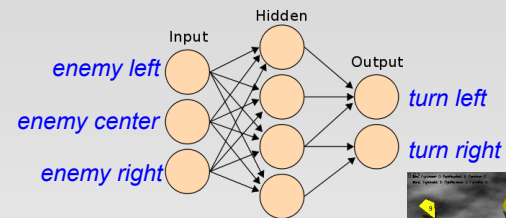
[show side-attack video]



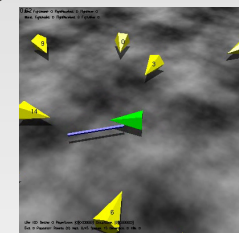
Combat Game Rules

- player swings bat (weapon)
 - if player hits bot with bat
 - bot is knocked back
 - and incurs 10 points damage
- if bot hits player (attacks with body)
 - player is knocked back
 - and incurs 10 points damage
 - player cannot swing bat while being knocked back
 - afterwards, is always facing direction of bot that hit it

Neural Net to Control Combat Bot

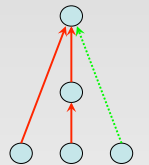


(NB: cannot sense other bots)

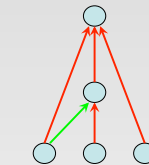


Neuroevolution of Combat Bots

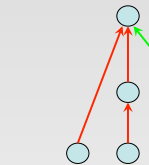
- Genetic representation is neural net
- Three types of mutations (no crossover used)



Perturb Weight



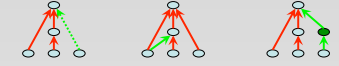
Add Connection



Add Node

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Neuroevolution of Combat Bots



- **Breeding**
 - each “parent” bot creates a clone (copy) of itself
 - clone is mutated with some small probability
 - each mutation type has different fixed probability
- **“Elitist” Selection**
 - combined population plays against simulated player
 - best scoring (most fit) half of combined population
 - become “parents” of next generation

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Supervised Learning - Player Simulation

Progression of three strategies (in order)

1. Spinning
 - player spins in place while swinging bat
 - to defeat this strategy, bots must learn to
 - wait until player’s back is turned,
 - then rush in and retreat
2. Alternating
 - player alternates between spinning and advancing
3. Chasing
 - player turns and moves toward closest bot
 - player and bots have same maximum speed

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Player Simulation (cont’d)

- Player progressed to next strategy when all of the following satisfied
 - average amount of damage *received* from bots (as a *group*) is consistently over 100
 - average amount of damage *inflicted* upon *single* bot was consistently less than 20
 - average time alive per bot was consistently over 850

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Contradictory Bot Objectives

1. maximize total damage to player (by the group)
 - requires coordination between bots (e.g., sacrifices)
2. minimize damage to self
 - the longer you live, the more chance you have to attack player
 - but you cannot just run away and stay safe

Three Fitness Measures

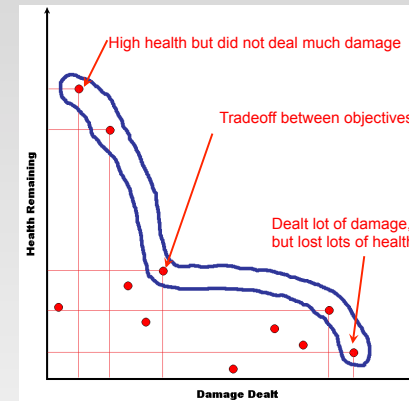
- Attack Score
 - all bots within small radius receive 10 points each time player is hit
 - bot that actually did the hit gets extra point
- Damage Received
 - negative 10 points for each hit received from bot
 - bot starts with 50 points (dead at zero)
- Time Alive
 - score is number of simulation time steps (0 – 900)
- *How to combine??*

Combining Fitness Measures

- Compared two approaches
 - single-objective
 - use single weighted score combining three measures
 - multi-objective
 - choose next parent population using “Pareto front”
- Multi-objective approach worked much better
 - evolves complex cooperative behaviors

Multi-Objective Optimization

- imagine a game with two objectives
- strategy **A dominates B** iff A is strictly better in one objective and at least as good in others
- population of points not dominated are best: **Pareto Front**



Experimental Method

- simulation run 30 times
- each run consisted of 3 populations of 15 bots (total population of 45 bots)
- 300 generations
- each generation consisted of 5 evaluations over which the fitness scores were averaged

Results

- Complex, successful populations evolved in which the following two behaviors were mixed:
 - *baiting* – one bot takes a risk in front so that rest can attack from the back and sides (“evolved altruism” ??) [\[see video\]](#)
 - *charging* – keep knocking player back before player can recover to swing bat [\[see video\]](#)

“Multi-objective evolution has found a good balance between objectives, in that bots are willing to risk a little damage in exchange for a higher assist bonus”

Future Directions

- evolve against humans
 - takes a long time (many generations)
 - maybe can “snapshot” old evolutionary states and switch between them?
- evolve against scripted behaviors to find weaknesses