Evolving Adaptation in Virtual Creatures

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The Problem: The simulated evolution of virtual creatures has produced many intriguing demonstrations, providing simple locomotion abilities and strategies for simple competetive games. However, to achieve a richer set of behaviours, adaptation within the individual's lifetime is being explored. Can evolution be used to learn domain specific rules for solving the credit assignment problem and suggesting which strategies to try next? This work aims to find out.

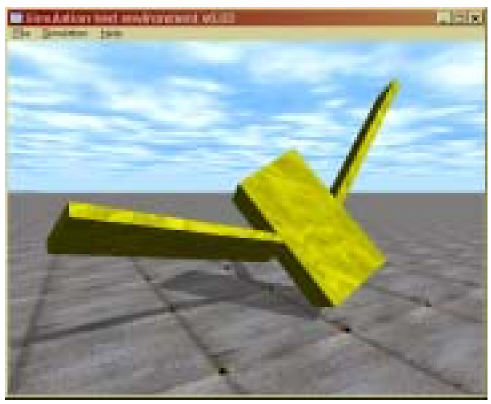

Figure 1: An evolved creature locomoting

Motivation: While robotics has made great advances, even the most advanced robots lack the flexibility and adaptability of living things. Previous work in evolving the bodies and brains of robots has demonstrated exciting results [2], but has so far only attempted simple behaviors such as walking or jumping.

Evolutionary computation typically creates individuals that are fixed during their lifetime, relying on the evolution itself to solve all problems. However, evolution gets only a very small amount of feedback, namely a single real number at the end of the individual's life. What's more, evolution doesn't attempt to solve the credit assignment problem, instead mutating every part of the genome with equal probability. Finally, given a partially successful individual, the children of that individual aren't constructed based knowledge learned about the problem domain, but rather by whatever is close in the representation.

Such evolved individuals are unable to adapt to circumstances that change during their lifetime. Reinforcement learning, on the other hand, suffers from poor generalization. When the value of a given state is determined, the programmer must decide which states are similar and so should have similar values. For example, if an individual is attacked by a striped tiger on a Tuesday by a particular palm tree, the programmer must have already determined whether the system will learn to avoid stripes, tigers, tuesdays, just that palm tree, or all palm trees. RL typically gets around this by experiencing so many episodes that every possible combination is evaluated several times. This can make training times very large.

Previous Work: Karl Simms performed early captivating work in this area [3], in which simple locomotion, point following, and competing to cover a block were evolved. More recently, a group at Brandeis has evolved similar creatures that are then automatically built on a shape deposition machine [2]. There has also been some work on the use of learning to adapt a neural network in an evolved creature [1].

Approach: The evolved bodies will be constrained to use parts typical of machines, such as rigid cylinders, metallic plates and electric motors. Rigid body simulators are well suited to this task, with Open Dynamics Engine being the simulator used in this work.

Previous work has largely focused on neural networks as the representation for brains, but an alternate representation could lead to behaviors of a much greater complexity. In particular, once a reasonably satisfactory gait or other behaviour is found, we often want to change behaviour under very limited circumstances. For example, we may want to put a limb down a little earlier in a very specific part of the gait, or shift the center of mass when a particular limb is three quarters extended. Changing output values in a limited area of the input space, while leaving outputs the same elsewhere, is difficult with neural networks, but easier with other representations. (In fact, this may be part of the reason for the success of tables and CMACS in reinforcement learning.) Thus, as a starting point, this work is using radial basis functions as a representation.

To affect these updates, simple feedback mechanisms will be evolved. For example, when trying to jump, a robot may be trying to maximize its kinetic energy in the period leading up to the actual jump. Finding actions that increase kinetic energy in the short term should be much easer than finding actions that maximize the creature's verical position over the entire run. As a starting point, this work simply evolves a function that, at each time step, gives the rate of change of one of the radial basis function parameters.

Impact: A success in this work could provide a powerful varient of machine learning, by esseintally allowing domain specific knowledge to be discovered by evolutionary computation and incorporated into a learning algorithm. This algorithm could work in higher dimentional spaces than reinforcement learning. The work could also point the way to giving important properties of living systems to machines, and shed light on the nature of those qualities.

References:

[1] David Ackley and Michael Littman. Interactions between learning and evolution. *Artificial Life II*, pages 487–509, 1992.

[2] H. Lipson and J.B. Pollack. *Nature*, pages 974–978, 2000.

[3] Karl Simms. Evolving 3d morphology and behavior by competition. *Artificial Life IV: Proceedings of the Fourth International Workshop on the Synthesis and Simulation of Living Systems*, pages 28–39, 1994.