Evolutionary Robotics

Motivations

Evolutionary Robotics is automatic generation of control systems and morphologies of autonomous robots. It is based on a process of Artificial Evolution without human intervention.

Two motivations:
- It is difficult to design autonomous systems using a purely top-down engineering process because the interaction between the robot and its environment is very complex and hard to predict.
  
  In ER the engineer defines the control components and the selection criterion and lets artificial evolution discover the most suitable combinations while the robot interacts with the environment.
- A synthetic (as opposed to an analytic) approach to the study of the mechanisms of adaptive behavior in machines and animals.

  ER was first suggested by a neurophysiologist (Braitenberg, 1984) as a way to show that evolution can generate simple artificial neural circuits that display apparently complex behaviors.
Evolution of Neural Networks

Genotype can encode:

1. **Connection Weights**: pre-defined network architecture, each weight encoded in separate genes (binary or real-valued), fixed-length genotype

2. **Topology**: variable-length genotype encodes presence/type of neurons and their connectivity

3. **Learning Rules**: fixed or variable length genotype encodes learning rules (constants of polynomial expression of x and y), not weights.

Evolution of Weights

Use real-valued or binary representation

Each synaptic weight is represented by one or more genes; e.g.:

Fitness function can be error, as in Back-Prop, or higher-level consequence of network output, such as behavior of a robot

Can be combined with learning:

- learning starts from genetically encoded weights
- fitness counts performance of network after training
- trained weights are **not** written back into genome
Collision-free Navigation

Fitness = V \times \Delta v \times (1-s)

Initial generation

After 45 generations

Companion slides for the book *Bio-Inspired Artificial Intelligence: Theories, Methods, and Technologies* by Dario Floreano and Claudio Mattiussi, MIT Press
The average and best population fitness are typical measures of performance.

Evolved robots always have a preferential direction of motion and speed.

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Homing for Battery Charge

Let us now put the robot in a more complex environment and make the fitness function even simpler. The robot is equipped with a battery that lasts only 20 s and there is a battery charger in the arena.

\[ \text{Fitness} = V \times (1-s) \]
After 240 generations, we find a robot capable of moving around and going to recharge 2 seconds before the batteries are completely discharged.

**Evolution of complex robots**

It is difficult to evolve from scratch large and complex robots because of:
- hardware robustness
- *bootstrap problem*

**Khepera**

**Koala**
**Incremental evolution**

A solution is to incrementally evolve robots from simple to complex. Simple robots gradually generates solutions that can be adapted to more complex robots faster and better than by starting with a complex robot.

\[
\text{Fitness} = V \times \Delta v \times (1-s)
\]

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**Incremental evolution results**

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Reinforcement Learning: Since Pavlov’s experiments with dogs, it has been known that positive and negative signals can be used to trigger learn association.

But is synaptic plasticity necessary to explain reinforcement learning?

Bynel and Floreano, 2003

T-maze problem

T-maze solving without learning
…and with real robots

Contrast Detection

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Vision-based Navigation

Fitness proportional to amount of forward translation over 2 mins

After 30 generations

Vision-based Blimp

- 5 x 5 room, random size stripes
- Fitness = forward motion (anemometer)
- 2 trials, 2 minutes each
- Evolution + network activation on PC
- Sensory pre-processing on microcontroller
Evolved behaviour

Evolved Control Strategy

Steering rate

- Turning rate from NN output
- Encoder turning rate

Amount of perceived contrast
Visual feature learning

Process whereby visual neurons become sensitive to certain sensory patterns (features) during the developmental process (Hubel & Wiesel, 1959)

Center-Surround

Oriented Edges

Hebb plasticity

image

Active vision

Process of selecting by motor actions sensory patterns (features) that make discrimination easier (Bajcsy, 1988)
**Active Vision**

- shape discrimination
- robot control
- car driving

- retina movement
- zooming factor
- filter type

**Goal:** Robot must move around simple arena using only vision information from a pan/tilt camera.

Output of vision system is movement of camera (pan/tilt) and of robot wheels (mot1/mot2). Filter as before.

**Robot Navigation**

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Fitness = percentage of covered distance D in R races on M circuits (limited time for each race).

\[ F = \frac{1}{R \times M} \sum_{r=1}^{R} \sum_{m=1}^{M} D_{r,m} \]
Vision based locomotion
Vision based locomotion

Evolution OF Learning

Synaptic learning rules can be genetically encoded. The rules are applied to the synaptic weights starting from random initial conditions.

Important aspects:
- A neural network can use different learning rules in different parts
- There is no need of teacher or reinforcement learning, no gradient descent and local minima
- Individuals are selected for their ability to learn, not simply to solve a specific problem
In addition, they perform well in different environments by developing suitable strategies. Contrary to conventional models, several synapses continue to change, but the overall pattern of change is dynamically stable.

**A Sequential Task**

A Khepera robot is evolved to switch on a light and go under the light, but this sequence of actions is not directly rewarded by the fitness function.

**Fitness** = \( \frac{\text{time}_{\text{gray}}_{\text{light}}}{\text{total}_{\text{time}}} \)
**Robustness to Color Change**

Evolved adaptive individuals can cope with new colours of the walls whereas genetically-determined individuals fail.

Similarly, evolved adaptive individuals transfer smoothly from simulated to real world.

Genetically-determined  Adaptive

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**Robustness to Layout Modification**

Evolved adaptive individuals can cope with new positions of the two landmarks whereas genetically-determined individuals cannot.

Genetically-determined  Adaptive
ANALOG GENETIC ENCODING (AGE)

DESIGNING AND UNDERSTANDING COMPLEX NETWORKS

Reward-based learning

Adapted from Niv et al., 2001

Blue flowers lead to a reward $x$
Yellow flowers lead to a reward $y$

fitness = $\sum$ rewards

Percentage of GREY colour under the cone-view
Percentage of BLUE colour under the cone-view
Percentage of YELLOW colour under the cone-view

Reward received upon landing
Landing signal
Evolved simulated bees

Fitness functions

Design of fitness functions that can generate desired behaviors is one of the most difficult parts of Evolutionary Robotics. Very often the evolved robot will maximize the fitness criterion using very simple behaviors.

Such evolved solutions can be interesting and surprising, but not what the engineer had in mind.

The choice of a fitness function makes all the difference between an optimization process and autonomous artificial life.
Fitness space

Fitness Space is a method to conceive and compare fitness functions.

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