

# Applying Evolutionary Computation to Robotics

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# The Big Picture

- **Problem:** A robot is faced with a problem where the solution is not immediately obvious
- **Potential Solution:** Evolutionary computation (EC) is a process which can solve difficult problems in programming
- **Issue:** Since a robot interacts with the physical world, EC is slower by many magnitudes
- **Solution:** By using simulation and applicable evolutionary strategies, it is possible to use EC to evolve robots

# Outline

- 1 Research Cases
  - Station Keeping Robot
  - Walking Robot
  - Coordinate Tracking Robot

2 Background

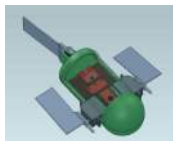
3 Simulation

4 Evolutionary Process

5 Results

6 Conclusion

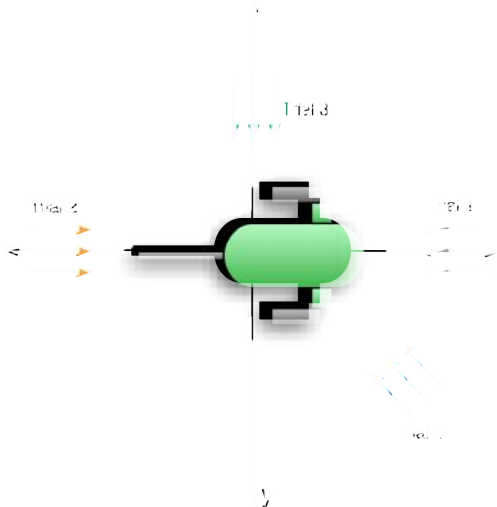
# Station Keeping Robot



Moore *et al.*

- Moore *et al.* developed the station keeping robot
- Goal: to maintain position in a body of water

# Station Keeping Robot



Moore *et al.*

# Walking Robot

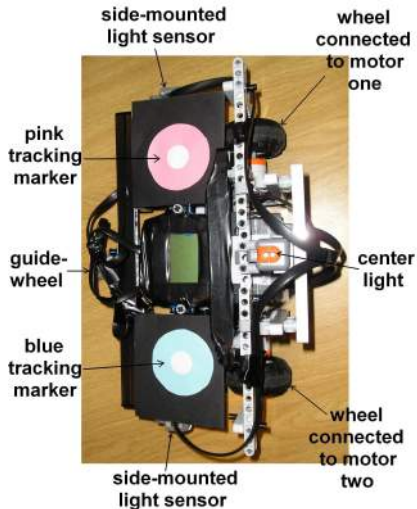
- Farchy *et al.* modified the code of the Aldebaran Nao robot
- Goal: to increase walking speed



Farchy *et al.*

# Coordinate Tracking Robot

- Pretorius *et al.* created a Lego Mindstorms robot
- Goal: to evolve an internal navigation controller



Pretorius *et al.*

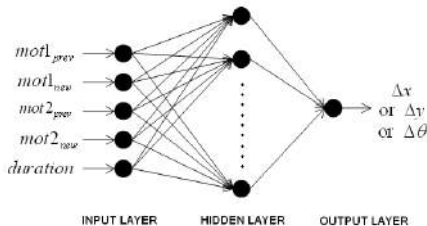
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  - Artificial Neural Networks
  - Evolutionary Computation
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# Artificial Neural Networks (ANN)

- ANNs are a collection of nodes with weighted edges.
- Input values are altered as they pass through nodes in the hidden layer based on the weights
- The purpose of the network is to develop a functional relationship from the input to the output



Pretorius *et al.*

# Evolutionary Computation

- Evolutionary Computation (EC) is a problem solving technique which mimics natural selection
- EC requires:
  - A candidate representation of a potential solution
  - A population of randomly generated candidates
  - A fitness function

# Evolutionary Computation: Process

- Candidates are evaluated
- The best performing candidates are selected
- Selected candidates undergo transformations to repopulate the population
- Process repeats until some limit is reached

# Outline

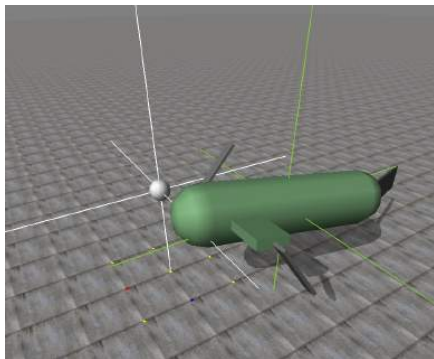
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# Simulation

- Defined as representing the characteristics or behaviors of one system through the use of another
- Error caused from inaccuracies of simulation is known as transitivity

# Station Keeping Robot: Simulation

- Used Open Dynamics Engine (ODE) to replicate the robot
- No fluid dynamics



Moore *et al.*

# Walking Robot: Simulation

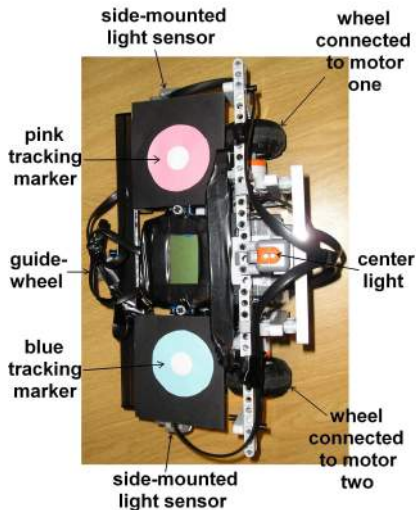
- Uses SimSpark (also ODE)
- Not a perfect representation



Farchy *et al.*

# Coordinate Tracking Robot: Simulation

- An overhead camera captured heading/orientation of robot from arbitrary motor commands
- A testbed of 5,000 commands were sent to the robot and captured by the camera, creating map of command and position



Pretorius *et al.*



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# Station Keeping Robot

- Evolved a separate candidate for each of the trials
- Population size of 100 candidates
- Evolved for 2,000 generations
- The entire process was repeated 25 times for each of the four trials
- Total: 20,000,000 runs (76.1 years real time)

# Station Keeping Robot: Neural Network

- Input:
  - Current 3D coordinates,  $(x, y, z)$
  - The difference between current and desired coordinate  $(x, y, z)$
  - The output of the previous output (servo speeds and oscillations)
- Output:
  - oscillation of the rear fin
  - speed of the left flipper
  - speed of the right flipper

# Station Keeping Robot: Fitness Function

$$\text{fitness} = \sum_t (10 - d_t(x, y, z))$$

where

$$d_t(x, y, z) = \begin{cases} 10, & \text{if distance}_t(x, y, z) > 10 \\ \text{distance}_t(x, y, z), & \text{otherwise} \end{cases}$$

# Walking Robot: Parameter optimization

- Farchy *et al.* wanted to optimize several parameters to increase speed

Parameter	Description
<i>stepPeriod</i>	Number of frames to take two steps.
<i>amp<sub>swing</sub></i>	Amplitude of the swing calculation.
<i>knee</i>	Base of the leg lifting calculation.
<i>startLength</i>	Used in calculating initial ramp up.
<i>v<sub>short</sub></i>	Factor for the leg lifting calculation.
<i>a<sub>short</sub></i>	Amplitude of the leg lifting calculation.
<i>φ<sub>short</sub></i>	Offset of the leg lifting calculation.
<i>v<sub>swing</sub></i>	Factor for the swing calculation.
<i>φ<sub>swing</sub></i>	Offset for the swing calculation.
<i>gyro<sub>hipPitch</sub></i>	Body pitch factor for calculating hip pitch.
<i>gyro<sub>kneePitch</sub></i>	Body pitch factor for calculating knee pitch.
<i>gyro<sub>hipRoll</sub></i>	Body roll factor for calculating hip roll.
<i>gyro<sub>ankleRoll</sub></i>	Body roll factor for calculating ankle roll.
<i>scale<sub>roll</sub></i>	Scale for sensor value of body roll.
<i>offset<sub>pitch</sub></i>	Offset for sensor value of body pitch.
<i>scale<sub>pitch</sub></i>	Scale for sensor value of body pitch.
<i>fwdOffset</i>	Offset to have the robot walk in place.

Farchy *et al.*

# Walking Robot: Fitness Functions

- Used two fitness functions for two separate runs
  - *omniWalk*

$$\text{fitness} = \left( \sum_t (\text{DistanceTraveled}_t) \right) - \text{fallingPenalty}$$

- *WalkFront*

$$\text{fitness} = \text{maxVelocity() in 15 seconds}$$

# Walking Robot: Grounded Simulation Learning

- Farchy *et al.* used Grounded Simulation Learning (GSL) when evolving candidates
- The point of GSL is to add human guidance in the evolution process
- This is done by examining the physical robot with an evolved candidate implementation, and isolating particular attributes

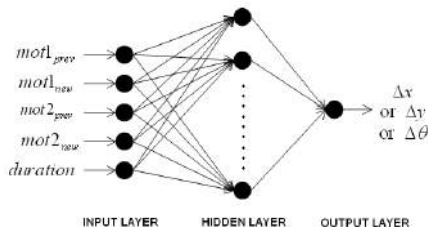
# Coordinate Tracking Robot

- Population of 250 candidates
- Evolved for 15,000 generations
- Process repeated three times for each ANN
- Total: 11,250,000 runs



# Coordinate Tracking Robot: Artificial Neural Network

- Inputs of the ANNs:
  - Current Motor speeds
  - Current length of time
  - Previous Motor speeds
- The ANN output was either:
  - The x-coordinate,
  - The y-coordinate,
  - And the angle



Pretorius *et al.*

# Coordinate Tracking Robot: Fitness Function

- Used the Mean Squared Error (MSE) as the fitness function

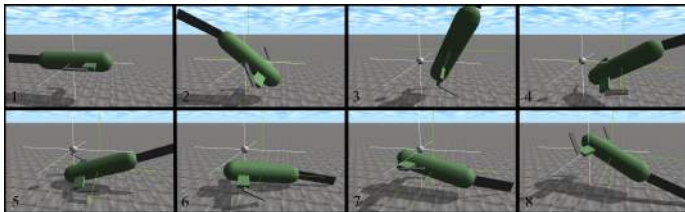
$$\text{fitness} = \frac{1}{N} \sum_{p=1}^N \sum_{i=1}^O (t_{pi} - a_{pi})^2,$$

- N is the size of the testbed (5,000)
- O is the ANN (1,2,3)
- t is the expected output (computed by ANN)
- a is the actual (testbed value)

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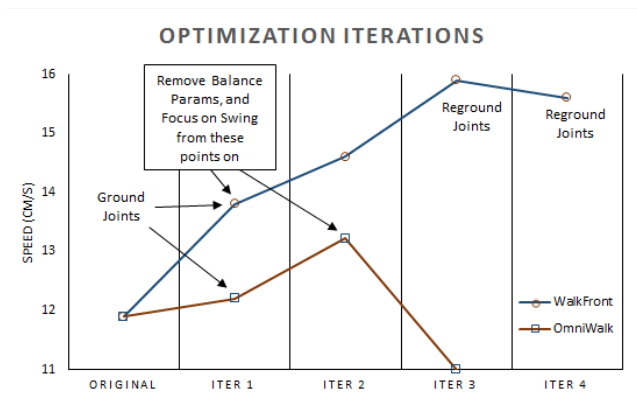
# Station Keeping Robot: Results



Moore et al.

- Each trial had a candidate which successfully maintained the position
- When the flow was coming from behind, the evolved candidate would flip end-over-head to orient itself (<http://y2u.be/UufbnEGFwV4>)

# Walking Robot: Results



Farchy *et al.*

# Coordinate Tracking Robot: Results

- Each of the ANNs evolved for 12 hours
- Pretorius *et al.* noted that the results were reasonably accurate

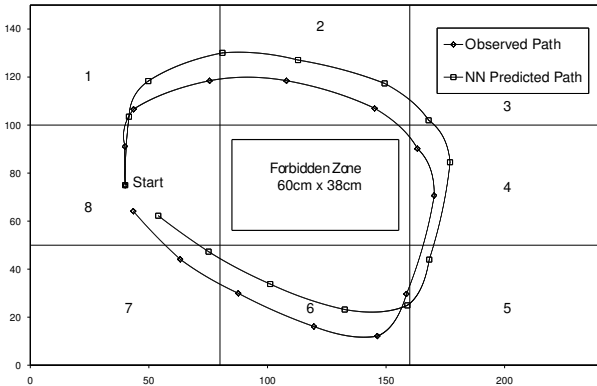
NN Simulator	Final MSE	Average absolute error
change in angle	26.412	3.585 degrees
change in y-coordinate	12.909	2.143 cm
change in x-coordinate	18.559	2.782 cm

Pretorius *et al.*

# Coordinate Tracking Robot: Navigation Test

- Using the evolved ANNs, a navigation test was made for a practical application
- The test was evolved to:
  - Drive the robot in a circle around a 3x3 grid,
  - Not leave the grid or touch the middle square

# Coordinate Tracking Robot: Results



Pretorius *et al.*



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# Conclusion

- By using a simulation, the evolutionary process can occur at a significantly faster rate
- Evolutionary robotics could be applied if:
  - the robotics problem is well defined,
  - the robot and environment can be simulated,
  - and an appropriate fitness function can be constructed



A. Farchy, S. Barrett, P. MacAlpine, and P. Stone.

Humanoid robots learning to walk faster: From the real world to simulation and back.

In Proceedings of the 2013 International Conference on Autonomous Agents and Multi-agent Systems, AAMAS '13, pages 39-46, Richland, SC, 2013.



J. M. Moore, A. J. Clark, and P. K. McKinley.

Evolution of station keeping as a response to flows in an aquatic robot.

In Proceeding of the Fifteenth Annual Conference on Genetic and Evolutionary Computation Conference, GECCO '13, pages 239-246, New York, NY, USA, 2013. ACM.



C. J. Pretorius, M. C. du Plessis, and C. B. Cilliers.

Towards an artificial neural network-based simulator for behavioral evolution in evolutionary robotics.

In Proceedings of the 2009 Annual Research Conference of the South African Institute of Computer Scientists and Information

Thank you for your time and attention!

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# Questions?