Evolutionary Robotics - An Overview

Bastian Lang

Master of Autonomous Systems

April 6, 2015

- Technique for the automatic creation of autonomous robots
- Inspired by darwinian principle of selective reproduction of the fittest
- Use of evolutionary algorithms and artificial neural networks
- Three major trends
  - Parameter tuning/ Neuroevolution
    - Use EA to tune parameters
  - Online evolutionary adaptation
    - Open-ended
  - Evolutionary synthesis
    - Body-brain evolution
- Tools
  - Evolutionary Algorithms
  - Simulated evolution
  - Embodied evolution

Mindmap

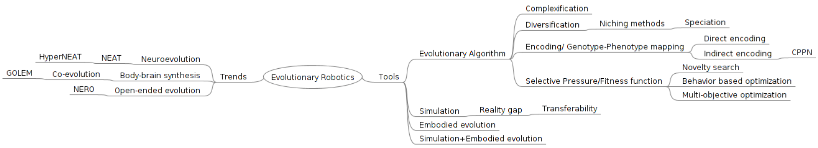

Figure : Mindmap ER

Fundamental Problems

- Neuroevolution
  - How to evolve neural networks for robot controlling tasks?
- The Reality Gap
  - Different behavior on real robot and on simulated one
- How to apply selective pressure?
  - How to evaluate an individual?
  - What is a good fitness function?
  - One goal vs multiple goals
  - Behavior based
  - Problems of fitness landscapes

Neuroevolution - Top 1 paper

Stanley, K. O., & Miikkulainen, R. (2002). Evolving neural networks through augmenting topologies. Evolutionary computation, 10(2), 99-127.

- Problem formulation
  - Artificial evolution of neural networks using genetic algorithms
- Deficits of the state of the art
  - Modifying structure of ANN has been efficient
  - Fixed topologies
  - Random initialization of hidden layers
- Approach taken
  - Global innovation number to make cross over possible
  - Complexification
  - Fitness sharing for diverse populations
- Evaluation and experimental results
  - Create XOR gates and double pole balancing
  - Comparison to best fixed structure methods so far → 8 times slower and not as successful
  - Explicitly test for cross over, complexification and fitness sharing → More evaluations needed and loss of success rate

Neuroevolution - Top 6 list

- Stanley, K. O., & Miikkulainen, R. (2002). Evolving neural networks through augmenting topologies. Evolutionary computation, 10(2), 99-127.
- Yao, X. (1999). Evolving artificial neural networks. Proceedings of the IEEE, 87(9), 1423-1447.
- Kashtan, N., & Alon, U. (2005). Spontaneous evolution of modularity and network motifs. Proceedings of the National Academy of Sciences of the United States of America, 102(39), 13773-13778.
- Angeline, P. J., Saunders, G. M., & Pollack, J. B. (1994). An evolutionary algorithm that constructs recurrent neural networks. Neural Networks, IEEE Transactions on, 5(1), 54-65.
- Clune, J., Beckmann, B. E., Ofria, C., & Pennock, R. T. (2009, May). Evolving coordinated quadruped gaits with the HyperNEAT generative encoding. In Evolutionary Computation, 2009. CEC'09. IEEE Congress on (pp. 2764-2771). IEEE.
- Harvey, I., Husbands, P., Cliff, D., Thompson, A., & Jakobi, N. (1997). Evolutionary robotics: the Sussex approach. Robotics and autonomous systems, 20(2), 205-224.

Reality Gap - Top 1 Paper

Koos, S., Mouret, J. B., & Doncieux, S. (2013). The transferability approach: Crossing the reality gap in evolutionary robotics. Evolutionary Computation, IEEE Transactions on, 17(1), 122-145.

- Problem formulation
  - Optimal solutions found in simulation perform significantly less good on real robot
  - Evolutionary algorithms exploiting faulty parts of simulations
  - Evolution on real robots is very time consuming and not always possible
- Deficits of the state of the art
  - Evolution on real robots is too slow
  - Assumptions that simulation optimum is similar to optimum in reality
  - Very accurate simulations are hard to create and computationally costly
  - Creating robust solutions will most likely end up in worse local optima
  - Human needed to help identify the dynamic system
- Approach taken
  - Create and update a surrogate model
  - Use simulation-to-reality mapping as additional goal to drop solutions that exploit errors of simulation.
- Evaluation and experimental results
  - Two wheeled robot that had to turn into the right direction at a T-cross depending on some light signals
  - Four-legged robot gait
  - Compared to purely simulation based approach with small variations, two reality based approaches and a noise-based approach
  - Simulation only performed much worse after transfer
  - Real robot based approaches bad in the first, quite good in the second experiment
  - Noise based approach better
  - Transferability best
  - Transferability does not correlate with robustness (behavior is not the same)

Reality Gap - Top 6 list

- Miglino, O., Lund, H. H., & Nolfi, S. (1995). Evolving mobile robots in simulated and real environments. Artificial life, 2(4), 417-434.
- Jakobi, N., Husbands, P., & Harvey, I. (1995). Noise and the reality gap: The use of simulation in evolutionary robotics. In Advances in artificial life (pp. 704-720). Springer Berlin Heidelberg.
- Koos, S., Mouret, J. B., & Doncieux, S. (2013). The transferability approach: Crossing the reality gap in evolutionary robotics. Evolutionary Computation, IEEE Transactions on, 17(1), 122-145.
- Jakobi, N. (1998, January). Running across the reality gap: Octopod locomotion evolved in a minimal simulation. In Evolutionary Robotics (pp. 39-58). Springer Berlin Heidelberg.
- Hartland, C., & Bredeche, N. (2006, December). Evolutionary robotics, anticipation and the reality gap. In Robotics and Biomimetics, 2006. ROBIO'06. IEEE International Conference on (pp. 1640-1645). IEEE.
- Toris, R. (2011). Evolving Robotic Desires: A New Approach to Bridging the Reality Gap (Doctoral dissertation, Dickinson College).

Fitness functions and selective pressure - Top 1 paper

Lehman, J., & Stanley, K. O. (2011). Abandoning objectives: Evolution through the search for novelty alone. Evolutionary computation, 19(2), 189-223.

- Problem formulation
  - Measuring progress
  - Strategies to explore the search space
  - Fitness functions usually used for this
- Deficits of the state of the art
  - Increasing fitness does not always reveal the best path through the search space
  - Objectives may lead to local optima
  - The more complex the goal, the harder to formulate
  - May ignore step stones to optimal solution
- Approach taken
  - Fitness based on novelty of behavior
  - Combined with NEAT solutions become more and more complex
  - Use metric to compute novelty as distance to other solutions
  - Keep track of all novel solutions
- Evaluation and experimental results
  - Compare novelty search to objective and random search
  - Two maps containing deceptive dead ends
  - First map novelty needed significantly less evaluations than NEAT with objective
  - Second map NEAT 3 out of 50, novelty 49 out of 50

Fitness functions and selective pressure - Top 6 list

- Lehman, J., & Stanley, K. O. (2011). Abandoning objectives: Evolution through the search for novelty alone. Evolutionary computation, 19(2), 189-223.
- Nelson, A. L., Barlow, G. J., & Doitsidis, L. (2009). Fitness functions in evolutionary robotics: A survey and analysis. Robotics and Autonomous Systems, 57(4), 345-370.
- Sareni, B., & Krhenbhl, L. (1998). Fitness sharing and niching methods revisited. Evolutionary Computation, IEEE Transactions on, 2(3), 97-106.
- Mouret, J. B., & Doncieux, S. (2012). Encouraging behavioral diversity in evolutionary robotics: An empirical study. Evolutionary computation, 20(1), 91-133.
- Jin, Y., Olhofer, M., & Sendhoff, B. (2002). A framework for evolutionary optimization with approximate fitness functions. Evolutionary Computation, IEEE Transactions on, 6(5), 481-494.
- Jin, Y., Olhofer, M., & Sendhoff, B. (2000, July). On Evolutionary Optimization with Approximate Fitness Functions. In GECCO (pp. 786-793).