

Bastian Lang

From MAS-Students_ss15

Topic: Real World Optimization of Energy Efficient Vehicle Control

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Date: 22-10-2015

Contents

- 1 Abstract
- 2 Introduction
- 3 Problem Formulation
 - 3.1 What is this project about?
 - 3.2 Why is it relevant?
 - 3.3 What have other people done in this field?
 - 3.4 Why is that not sufficient?
 - 3.5 What is the deficit addressed in this project?
- 4 State of the Art
 - 4.1 Essays
 - 4.1.1 Evolving Look Ahead Controllers for Energy Optimal Driving and Path Planning
 - 4.1.2 Evolving neural networks through augmenting topologies
 - 4.1.3 Explicit Fuel Optimal Speed Profiles for Heavy Trucks on a Set of Topographic Road Profiles
 - 4.2 Reading Reports
 - 4.2.1 The transferability approach: Crossing the reality gap in evolutionary robotics
 - 4.2.2 Noise and the reality gap: The use of simulation in evolutionary robotics
 - 4.2.3 Evolving coordinated quadruped gaits with the HyperNEAT generative encoding

- 4.2.4 paper_title (todo)
- 4.2.5 paper_title (todo)
- 4.2.6 paper_title (todo)
- 4.2.7 paper_title (todo)
- 4.2.8 paper_title (todo)
- 4.2.9 paper_title (todo)
- 4.2.10 paper_title (todo)
- 4.2.11 paper_title (todo)
- 4.3 Conclusions
- 4.4 References
- 4.5 Appendix
 - 4.5.1 A. Online literature search
 - 4.5.2 B. Sources
 - 4.5.3 C. List of top research labs/researchers

Abstract

Introduction

Problem Formulation

What is this project about?

- Creating an energy efficient vehicle control for a real-world vehicle

Why is it relevant?

- Energy-efficiency is important in transportation as even small improvements result in huge savings of energy
- There is still much room for improvements as even simple driver-training programs have yielded impressive results

What have other people done in this field?

- Use of optimal control theory
- Use of graph search algorithms
- Use of heuristics to prune search space
- Use of inverted system equations to avoid discretization
- Application of evolutionary algorithms to evolve a controller in simulation

Why is that not sufficient?

- Complexity and computation speed is not good enough for real time application
- Not all system equations can be inverted and it is non-trivial
- Vehicle control only developed in simulation without preparations for transfer to real world
- Transfer algorithms do not have many real world applications so far, only proof of concepts

What is the deficit addressed in this project?

- The controller so far has only been developed in simulation and not on the real device

State of the Art

Essays

Evolving Look Ahead Controllers for Energy Optimal Driving and Path Planning

Full reference: Gaier, A., & Asteroth, A. (2014, June). Evolving look ahead controllers for energy optimal driving and path planning. In Innovations in Intelligent Systems and Applications (INISTA) Proceedings, 2014 IEEE International Symposium on (pp. 138-145). IEEE.

Abstract: An evolved neural network controller is presented to solve the optimal control problem for energy optimal driving. A controller is produced which computes equivalent control commands to traditional graph searching approaches, while able to adapt to varied constraints and conditions. Furthermore, after training, trivial amounts of computation time and memory are required, making the approach applicable for embedded systems and path planning applications.

Keywords:

Problem formulation

- Developing techniques for near energy-optimal control of vehicles using controllers that base their decisions on characteristics of the road.
- Developing control strategies that make the best use of the terrain.

Why is this still a problem?

- Engineering of transport systems resulted in efficient designs, but further optimizations are diminishing.
- Driver-training programs have yielded impressive results.
- Instead of being reduced, emissions caused by transportation drastically increased in 2005 and 2007.

State of the art

Energy-optimal control of commercial trucks and trains

- Energy-optimal control of experimental vehicles
- Energy-optimal control of hybrid gas-electric vehicles
- Finding fuel-optimal behavior of an experimental fuel-cell vehicle using optimal control theory and a simplified model of environment and vehicle

- It was found that only three commands are needed to produce an optimal strategy:
 - full power
 - maintain velocity
 - coast
- Reformulating the problem as a graph-search problem using A* and a special heuristic the number of nodes needed could be drastically decreased with still achieving nearoptimal solutions
- Using dynamic programming to reduce complexity and rounding errors from state space discretisation
- Using inverted system equations real valued controls could be used. But not all equations can be inverted and it is often non-trivial
- Avoiding numerical issues by first defining the boundary line between feasible and infeasible states. This reduced computation costs by an order of magnitude.
- Neuroevolution techniques have shown to be more effective on some benchmark tests than reinforcement learning techniques
- NEAT is the current most successful algorithm within neuroevolutionary algorithms

What is the author's contribution?

- Use of evolutionary algorithms instead of graph search algorithms
- Application of a state-of-the-art evolutionary algorithm to the energy-optimal control problem

How did the author's solution solve the addressed problem?

- By using the method of NEAT (NeuroEvolution of Augmented Topologies) the authors evolve a controller for an e-bike
- Use of simplified vehicle model
- Use of three motor commands
- Evolutionary algorithms do not need to work in a discretized state space, so rounding errors are no problem
- Evolutionary algorithms do not use state space models. Therefore increasing the complexity of the model does not have a huge effect on the space complexity.
- Using a local solution that calculates new commands at every meter, a degree of precision can be achieved that is not possible for graph search in most scenarios.

Evaluation

- Comparison of performance on 35 routes with a Graph Search algorithm
- Training of net using cross-validation
- Training on 5 maps, testing on remaining 30
- 50 training runs, each containing of evolving a population of size 150 for 1000 generations.
- Comparison to graph search in three different resolution levels
- Performance is only slightly worse than the highest depth graph.
- Analysed in detail most solutions performed better
- Computation time was nearly instantaneous versus about 1 minute for an 8km route
- Space complexity was about 1KB versus 11GB

What are the scientific deficits of this approach?

- The approach taken uses a very popular algorithm from evolutionary algorithms, but it does not use any techniques to ensure that the evolved controller will be able to run on a real device. Where the authors can give a prove f concept that an evolutionary algorithm may be better suited than a graph search approach, like this it probably is not usable in practise. Although giving prove of concept was the author's goal and this is not a scientific deficit but a shortcoming of this approach so far.
 - 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 Trans-actions on*, 17(1), 122-145.

What are the scientific contributions of this approach?

- The authors were able to show that using evolutionary algorithms for optimizing energy-efficient driving outperforms graph search algorithms in terms of computation time and space needed and produces solutions that are nearly as optimal as solutions from very detailed graph search algorithms.
- As for this paper is very recent (2014) I am not able to quote any other work that supports my statement. Citeseer does not know this paper yet and google just gives one quote from a paper of the same authors.

Evolving neural networks through augmenting topologies

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

Abstract: An important question in neuroevolution is how to gain an advantage from evolving neural network topologies along with weights. We present a method, NeuroEvolution of Augmenting Topologies (NEAT), which outperforms the best fixed-topology method on a challenging benchmark reinforcement learning task. We claim that the increased efficiency is due to (1) employing a principled method of crossover of different topologies, (2) protecting structural innovation using speciation, and (3) incrementally growing from minimal structure. We test this claim through a series of ablation studies that demonstrate that each component is necessary to the system as a whole and to each other. What results is significantly faster learning. NEAT is also an important contribution to GAs because it shows how it is possible for evolution to both optimize and complexify solutions simultaneously, offering the possibility of evolving increasingly complex solutions over generations, and strengthening the analogy with biological evolution.

Keywords:

What is the paper about?

- A new algorithm called NEAT for neuroevolution (NE), i.e. the design of the topology and the parameters of an artificial neural network using evolutionary techniques

Why is this relevant?

- NE has shown to be faster and more efficient than reinforcement learning methods on tasks as single pole-balancing and robot arm control
- NE is effective in continuous and high dimensional state spaces
- Memory can easily be represented through recurrent neural networks, which makes NE a natural choice for non-Markovian tasks.

What have others done and why is this not sufficient?

- Topology of ANN chosen before the experiment
- Research on algorithms that evolved the topology/structure of an ANN provided inconclusive answers about why evolving the topology is superior to using fixed topologies
 - Evolving topology lead to solving the hardest pole-balancing task so far, but could be achieved with randomly initialized topologies afterwards five times faster.
- Evolving topology and weights significantly enhances the performance of NE

What have the authors done and why is this better?

- Introduction of NeuroEvolution of Augmented Topologies (NEAT)
 - Use of historical markings to keep track of the same genes in different solutions -> Allows for an easy and meaningful application of the cross-over operator
 - Using speciation, i.e. compute the similarity of solutions and share their fitness if similar enough → Protection of new innovative solutions to give them time to develop their potential
 - Start with minimal solution and grew them more and more complex -> Algorithm will search low dimensional search space first which enhances performance

Evaluation

- Comparison to SOA approaches in the creation of XOR gates -> NEAT could outperform the other methods
- Comparison to SOA approaches in a double pole-balancing task -> NEAT could outperform the other methods
- Tested necessity of cross-over -> Significantly more evaluations needed to find a solution
- Tested necessity of speciation -> Failure in about 25% and about seven times more runtime
- Tested necessity of complexification -> Fixed ANN successful in about 20% and about

8.5 times slower

What are the scientific deficits of this approach?

What are the scientific contributions of this approach?

- Method to optimize architecture and weights – Chen, Yuehui, et al. "Time-series forecasting using flexible neural tree model." Information sciences 174.3 (2005): 219-235.
 - Whiteson, Shimon, and Peter Stone. "Evolutionary function approximation for reinforcement learning." The Journal of Machine Learning Research 7 (2006): 877-917.
 - Clune, Jeff, et al. "Evolving coordinated quadruped gaits with the HyperNEAT generative encoding." Evolutionary Computation, 2009. CEC'09. IEEE Congress on. IEEE, 2009.
 - Approach to overcome "course of dimensionality"
 - Togelius, Julian, et al. "Search-based procedural content generation: A taxonomy and survey." Computational Intelligence and AI in Games, IEEE Transactions on 3.3 (2011): 172-186.
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Explicit Fuel Optimal Speed Profiles for Heavy Trucks on a Set of Topographic Road Profiles

Full reference: Froeberg, Anders, Erik Hellstroem, and Lars Nielsen. Explicit fuel optimal speed profiles for heavy trucks on a set of topographic road profiles. No. 2006-01-1071. SAE Technical Paper, 2006.

Abstract: The problem addressed is how to drive a heavy truck over various road topographies such that the fuel consumption is minimized. Using a realistic model of a truck powertrain, an optimization problem for minimization of fuel consumption is formulated. Through the solutions of this problem optimal speed profiles are found. An advantage here is that explicit analytical solutions can be found, and this is done for a few constructed test roads. The test roads are constructed to be easy enough to enable analytical solutions but still capture the important properties of real roads. In this way the obtained solutions provide explanations to some behaviour obtained by ourselves and others using more elaborate modeling and numeric optimization like dynamic programming.

The results show that for level road and in small gradients the optimal solution is to drive with constant speed. For large gradients in downhill slopes it is optimal to utilize the kinetic energy of the vehicle to accelerate in order to gain speed. This speed increase is used to lower the speed on other road sections such that the total average speed is kept. Taking account for limitations of top speed the optimal speed profile changes to a strategy that minimizes brake usage. This is done by e.g. slowing down before steep down gradients where the truck will accelerate even though the engine does not produce any torque.

What is the paper about?

- How to drive a truck such that the fuel consumption is minimized?
- Finding an optimal strategy.
- Understanding of the energy usage of a heavy truck.
- Proving the correctness of previous results mathematically.

Why is this relevant?

- Fuel is a large part of the operating costs of heavy trucks. Reducing the need could save money.

What have others done and why is this not sufficient?

- Use of simple models.
- Use optimal control theory approach (e.g. dynamic programming) -> approximate solutions

What have the authors done and why is this better?

- Analytical derivation of efficient driving behaviour using a physical model of a heavy truck that can predict the fuel consumption while being manageable complex.
- Used model is very accurate and consists of:
 - Engine
 - Transmission
 - Final Gear
 - Wheels and Chassis
- Using this model and their mathematical approach, the results and derived behaviours are very accurate.

Evaluation

- The authors did not do a an evaluation in the sense of a simulation or real world experiments. Instead they created the physical model of a heavy truck and derived different optimal behaviour for different situations.
- They showed that:

- for level roads maintaining a constant speed is optimal
- for small gradients maintaining a constant speed is optimal
- for steep uphill slopes maximum fuelling is optimal
- for steep downhill slopes cutting off fuel until desired velocity is reached afterwards is optimal
- when considering a maximum speed cutting of fuel to decelerate some time before the downhill slope to reach maximum velocity at the end of the slope is optimal. This point can be calculated.

What are the scientific deficits of this approach?

- No use of other economic factors apart from fuel consumption
 - Passenberg, Benjamin, Peter Kock, and Olaf Stursberg. "Combined time and fuel optimal driving of trucks based on a hybrid model." Control Conference (ECC), 2009 European. IEEE, 2009.
- Not applicable to unknown tracks
 - Sahlholm, Per, et al. "A sensor and data fusion algorithm for road grade estimation." 5th IFAC Symposium on Advances in Automotive Control (2007). 2007.

What are the scientific contributions of this approach?

- Energy optimal control can be achieved using only three motor commands:
 - Full Power
 - Maintain Velocity
 - Coast
 - Ivarsson, Maria, Jan Aslund, and Lars Nielsen. "Look-ahead control-consequences of a non-linear fuel map on truck fuel consumption." Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile engineering 223.10 (2009): 1223-1238.
 - Gaier, Adam, and Alexander Asteroth. "Evolving look ahead controllers for energy optimal driving and path planning." Innovations in Intelligent Systems and Applications (INISTA) Proceedings, 2014 IEEE International Symposium on. IEEE, 2014.
 - Sahlholm, Per, et al. "A sensor and data fusion algorithm for road grade estimation." 5th IFAC Symposium on Advances in Automotive Control (2007). 2007.
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Reading Reports

The transferability approach: Crossing the reality gap in evolutionary robotics

Full reference: Koos, Sylvain, Jean-Baptiste Mouret, and Stéphane Doncieux. "The transferability approach: Crossing the reality gap in evolutionary robotics." *Evolutionary Computation, IEEE Transactions on* 17.1 (2013): 122-145.

Abstract: The reality gap, which often makes controllers evolved in simulation inefficient once transferred onto the physical robot, remains a critical issue in evolutionary robotics (ER). We hypothesize that this gap highlights a conflict between the efficiency of the solutions in simulation and their transferability from simulation to reality: the most efficient solutions in simulation often exploit badly modeled phenomena to achieve high fitness values with unrealistic behaviors. This hypothesis leads to the transferability approach, a multiobjective formulation of ER in which two main objectives are optimized via a Pareto-based multiobjective evolutionary algorithm: 1) the fitness; and 2) the transferability, estimated by a simulation-to-reality (STR) disparity measure. To evaluate this second objective, a surrogate model of the exact STR disparity is built during the optimization. This transferability approach has been compared to two reality-based optimization methods, a noise-based approach inspired from Jakobi's minimal simulation methodology and a local search approach. It has been validated on two robotic applications: 1) a navigation task with an e-puck robot; and 2) a walking task with a 8-DOF quadrupedal robot. For both experimental setups, our approach successfully finds efficient and well-transferable controllers only with about ten experiments on the physical robot.

Reading Report

This paper deals with the problem of the reality gap and introduces an approach to overcome this problem. One major problem of evolutionary robotics is that good or optimal solutions for controllers found via evolution in simulation transformed onto the real robot perform significantly less good. According to the authors this may be because of inaccurate simulations and evolutionary algorithms exploiting these faulty parts of simulations. But evolution on real robots is very time consuming and therefore not possible for most scenarios.

The authors suggest an approach that tries to only rely on the accurate parts of the simulation. To achieve this they introduce a value that indicates how well a solution transfers to the reality. This is called the

transferability approach.

The approach creates and updates a surrogate model that maps a controller to a transferability value which describes how close the simulated behaviour is to the behaviour when transferred to the real robot. The search for a good controller is thus a multi-objective optimization. The fitness of a controller is determined by its behavioural fitness together with its transferability and its diversity.

Every now and then one promising controller of a population is transferred to the real robot and the surrogate model is updated. This approach uses only a few experiments on the real robot by searching for good solutions in simulation and reality while avoiding to exploit inaccuracies of the simulation.

The authors tested their approach in two experiments and compared it to some other approaches. They compared it to purely simulation based approaches with small variations, to two reality based approaches and to a noise-based approach introduced by Jakobi et Al.

The first experiment was performed on a two wheeled robot that had to turn into the right direction at a T-cross depending on some light signals. The second experiment was performed on a four-legged robot to create a controller for moving.

In both experiments the approaches based on simulation only (or with performing only a few experiments on the real robot afterwards) experienced the most problems with the reality gap. They performed much worse when transferred into reality. The real robot based approaches performed bad in the first, but quite good in the second experiment, probably because task was easier in the second experiment. The noise-based approach performed better than those former approaches, but overall the transferability approach provided the best solutions.

A closer analysis of the robustness of a solution and its transferability showed that the correlation is low, meaning that a robust solution is not a solution that can behaves similar in reality and vice versa.

Scientific Deficits

Scientific Contributions

Noise and the reality gap: The use of simulation in evolutionary robotics

Full reference: Jakobi, Nick, Phil Husbands, and Inman Harvey. "Noise and the reality gap: The use of simulation in evolutionary robotics." *Advances in artificial life*. Springer Berlin Heidelberg, 1995. 704-720.

Abstract: The pitfalls of naive robot simulations have been recognized for areas such as evolutionary robotics. It has been suggested that carefully validated simulations with a proper treatment of noise may overcome these problems. This paper reports the results of experiments intended to test some of these claims. A simulation was constructed of a two-wheeled Khepera robot with IR and ambient light sensors. This included detailed mathematical models of the robot-environment interaction dynamics with empirically determined parameters. Artificial evolution was used to develop recurrent dynamical network controllers for the simulated robot, for obstacle-avoidance and light-seeking tasks, using different levels of noise in the simulation. The evolved controllers were down-loaded onto the real robot and the correspondence between behaviour in simulation and in reality was tested. The level of correspondence varied according to how much noise was used in the simulation, with very good results achieved when realistic quantities were applied. It has been demonstrated that it is possible to develop successful robot controllers in simulation that generate almost identical behavior in reality, at least for a particular class of robot-environment interaction dynamics.

Reading Report

In other related work there have been made some assumptions about what has to be fulfilled to result in as small a gap of performance between simulation and reality with respect to evolutionary robotics. This study takes some of these assumptions and tests them in some experimental settings.

When transferring evolved control systems for mobile robots from simulation to real robots it could often be observed that the robot performs much worse than in the situation. Related studies have suggested several methods to keep this reality gap as small as possible. Two of them are the careful design of the simulator by using empirical data and the use of noise and noise resistant control systems such as neural networks.

The authors of this study use the Khepera robot to evolve neural control systems for obstacle avoidance and light seeking behavior and then analyze the effect of noise applied to the simulation on the resulting behavior of the real robot.

The Khepera robot is a small, cylindrical robot with six front and two back infra-red sensors which can also be

used in another mode to sense ambient light. The robot has been developed to enable users to use and test their own control systems. The simulation used in the experiments was built using empirical data from the real Khepera robot to model the input of the sensors and the effects of the actuators. The controlling neural net has been evolved using artificial evolution.

In their experiments the authors used three different levels of noise: none, Gaussian distributed according to empirical data and Gaussian distributed with double standard deviation. They tested those noise levels in two different scenarios: Obstacle avoidance and light seeking. In the obstacle avoidance scenario the robot had to drive as fast and as straight lined as possible while avoiding pillars placed in an arena. In the light seeking scenario the robot had to reach a light source mounted on one wall of an empty arena. For comparing the simulated and the real robot's behavior the authors used some video processing technique to obtain the trajectory of the real robot.

Using double deviated noise or no noise at all resulted in bad performances for both tasks, obstacle avoidance and light seeking. The best results have been made for the noise level similar to that of the real environment.

The authors could be convinced that it is possible to transfer from simulation to real robots without losing much performance, but they are still skeptical if this still holds for more complex tasks.

Scientific Deficits

Scientific Contributions

Evolving coordinated quadruped gaits with the HyperNEAT generative encoding

Full reference:

Clune, Jeff, et al. "Evolving coordinated quadruped gaits with the HyperNEAT generative encoding." Evolutionary Computation, 2009. CEC'09. IEEE Congress on. IEEE, 2009.

Abstract:

Legged robots show promise for complex mobility tasks, such as navigating rough terrain, but the design of

their control software is both challenging and laborious. Traditional evolutionary algorithms can produce these controllers, but require manual decomposition or other problem simplification because conventionally-used direct encodings have trouble taking advantage of a problem's regularities and symmetries. Such active intervention is time consuming, limits the range of potential solutions, and requires the user to possess a deep understanding of the problem's structure. This paper demonstrates that HyperNEAT, a new and promising generative encoding for evolving neural networks, can evolve quadruped gaits without an engineer manually decomposing the problem. Analyses suggest that HyperNEAT is successful because it employs a generative encoding that can more easily reuse phenotypic modules. It is also one of the first neuroevolutionary algorithms that exploits a problem's geometric symmetries, which may aid its performance. We compare HyperNEAT to FT-NEAT, a direct encoding control, and find that HyperNEAT is able to evolve impressive quadruped gaits and vastly outperforms FT-NEAT. Comparative analyses reveal that HyperNEAT individuals are more holistically affected by genetic operators, resulting in better leg coordination. Overall, the results suggest that HyperNEAT is a powerful algorithm for evolving control systems for complex, yet regular, devices, such as robots.

Reading Report

This paper is about the creation of a modular neural net controller for quadruped gait using generative encodings.

In the introduction the authors motivate their work by some facts found in other studies and by the lack of studies focused on this particular objective. Related studies showed that by using generative encodings more complex and modular phenotypes can be produced. Also modular neural networks tend to evolve more effective gaits for legged robots. There have been studies using generative encodings, but those did not focus on the use of modular neural networks or did not have the computational possibilities to sufficiently produce data to prove their results.

The generative encoding used in the paper is called HyperNEAT, which uses the principles of the NeuroEvolution of Augmented Topologies (NEAT) algorithm. It produces Compositional Patterns Producing Networks (CPPNs). Evolving CPPNs exhibits the repetition of themes, symmetries and hierarchies, with and without variation. CPPNs can be used to generate neural networks. Mutation is used to change the CPPNs. The NEAT algorithm can be applied to the CPPNs, because their structure is similar to a population of neural networks. NEAT is unique in three main ways:

- It starts with small genomes that encode simple networks and slowly makes them more complex via mutation (adding of nodes).
- It uses a fitness-sharing mechanism that preserves diversity in the
- It uses historical information to perform crossover in an effective way.

As a control algorithm in the experiments another implementation of NEAT is used, the so called Fixed-Topology NEAT (FT-NEAT), which uses a direct encoding.

The results of the experiments show HyperNEAT vastly outperforming FT-NEAT at every generation. Also experiments had to be stopped eventually due to computational reasons, it seemed unlikely for FT-NEAT to close up to HyperNEAT afterwards. Interesting is the difference in fitness in the very first generation. Even randomly generated CPPNs are sometimes able to produce the coordination of legs that facilitates movement.

In the end, the solutions of HyperNEAT very often produced synchronized motion between the legs. Also reappearing patterns occurred. The results of FT-NEAT were not unable to come up with synchronization or repeating patterns, but it was much more uncommon. Most solutions of FT-NEAT fell over eventually. Looking at the joint values over time the joints of HyperNEAT are far more coordinated. Mutations to a generative encoding tend to be much less damaging when simultaneously evolving morphologies and controllers. Also studying the effects of mutation and crossover when appeared solely showed that the effect of mutation was much more beneficial to HyperNEAT than to FT-NEAT. Having a closer look at crossover, HyperNEAT far more created offspring whose fitness lied between those of its parents. The reasons have yet to be analysed.

Summarizing HyperNeat created far better results. One reason is the ability to reuse neural modules and thus more easily coordinate the behaviours of a robots leg. Another reason might be the ability of HyperNEAT to exploit symmetry.

Scientific Deficits

Scientific Contributions

paper_title (todo)

Full reference: todo

Abstract: todo

Keywords: todo

Did the authors provide a clear problem formulation and what exactly is the problem addressed in the paper?

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Did the authors argue why the studied problem is still a problem and what were their arguments?

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Did the authors make sufficiently clear what their own contributions is and if so, what exactly is their contribution?

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Did the authors make clear how their solutions solves the addressed problem and how it outperforms previous solutions?

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Did the authors describes in sufficient detail how they evaluated their approach?

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What are the scientific deficits of this approach?

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What are the scientific contributions of this approach?

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paper_title (todo)

Full reference: todo

Abstract: todo

Keywords: todo

Did the authors provide a clear problem formulation and what exactly is the problem addressed in the paper?

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Did the authors argue why the studied problem is still a problem and what were their arguments?

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Did the authors provide a reasonably comprehensive state of the art analysis?

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Did the authors make sufficiently clear what their own contributions is and if so, what exactly is their contribution?

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Did the authors make clear how their solutions solves the addressed problem and how it outperforms previous solutions?

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Conclusions

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References

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Appendix

A. Online literature search

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B. Sources

""B.1 List of searched journals

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""B.2 List of searched conference proceedings

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'''B.3 List of searched magazines

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'''B.4 Other searched publications

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C. List of top research labs/researchers

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