Robotics and
Embedded Systems

5G Network Analysis

Project Report for the Lab Course Sensor Model-Based Autonomous Driving

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1. Introduction

Gaits are challenging and time-consuming to design manually. To design effective gaits knowledge on expert level would be mandatory. An alternative to solve this challenging task is to exploit machine learning techniques to evolve gaits on a robot. In this case a genetic algorithm, which mimics natural selection in biological evolution, is well suited for selecting the best evolving gaits. The goal is to learn a sequence of joint configurations on a robot's legs that lead to a preferably effective gait. A genetic algorithm seems the logical choice for this complex task since it mimics the natural learning behavior. A robot with legs learns to evolve gaits analog to animals. In short, the idea is to evolve many generations of gaits in a simulation to get efficient forward-moving gaits on a quadrupedal robot, called ALLBOT (see figure 1).

Figure 1 ALLBOT robot (left) and an isometric representation (right). Each leg has two servo actuated joints resulting in a total of eight degrees of freedom. (sources: `https://cdn-reichelt.de/bilder/web/xxl_ws/C160/ALLBOT_4_LEG_01.png`, `http://www.allbot.eu/connect/manuals/`)

This thesis is structured in the following manner: First the ALLBOT robot is simulated with the robot simulation software Gazebo to avoid time-consuming training on the physical robot or suffering from mechanical failure during training. The simulation setup is described in chapter 3. Since the gaits are evolved with the deep learning genetic algorithm HyperNEAT, the theoretical background to HyperNEAT is summarized in chapter **??**. The setup and parameters of the HyperNEAT algorithm as well as its implementation details are described in chapter **??**. Results are described in chapter **??** before conclusions are drawn in chapter 4.

2. Model

Hypercube-based NeuroEvolution of Augmenting Topologies (HyperNEAT) is an indirect encoding for evolving artificial neuronal networks (ANNs).

The HyperNEAT algorithm, as illustrated in figure 2, consists of three major components:

(i) A Compositional Pattern Producing Network (CPPN) that acts as a genome.

(ii) A genetic NEAT algorithm that evolves the CPPN.

(iii) An artificial neural network (ANN) that acts as a phenotype.

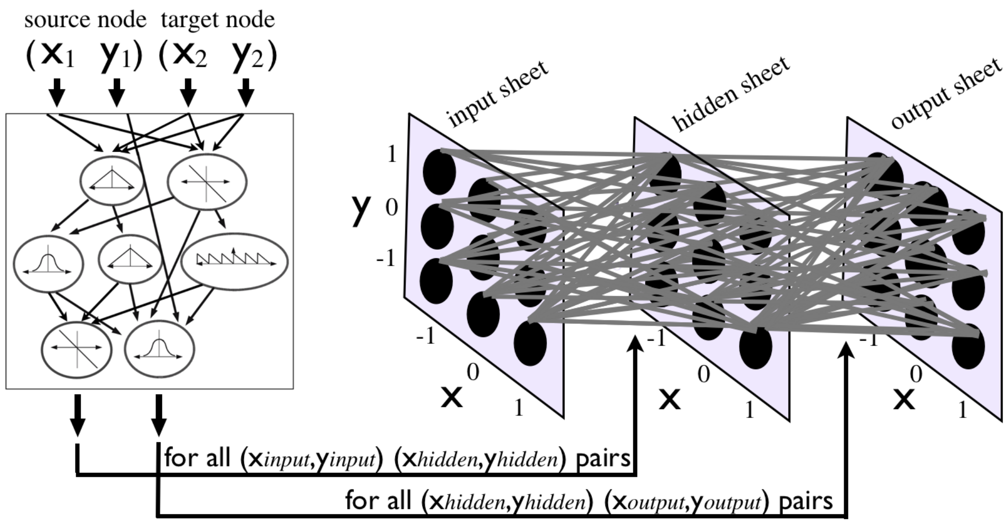

Figure 2 Illustration of the HyperNEAT algorithm [2]. A CPPN (left) which is evolved with the NEAT algorithm encodes an ANN (right).

3. Simulation

3.1. Sub

Blub blub

3.2. Blub

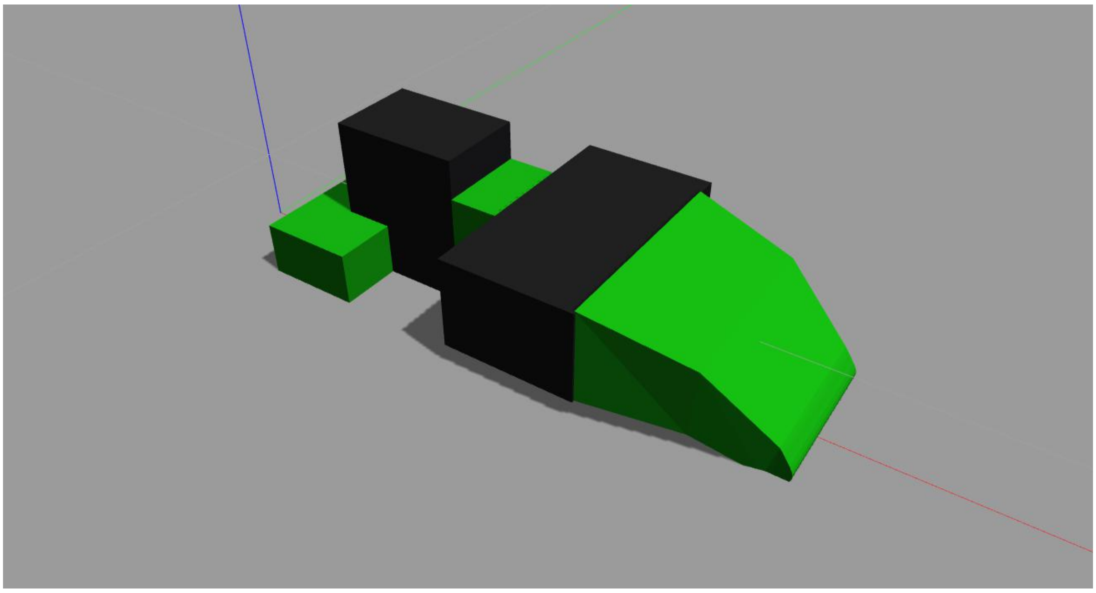

Figure 3 Rendering of the cuboid leg model with simplified foot mesh.

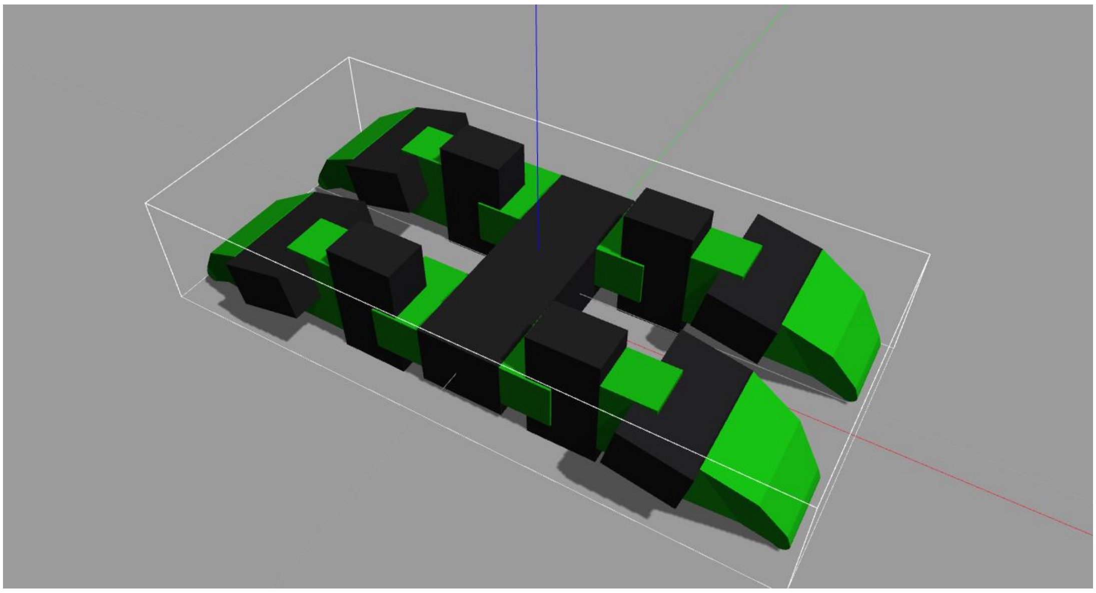

Figure 4 Rendering of the cuboid robot model in Gazebo.

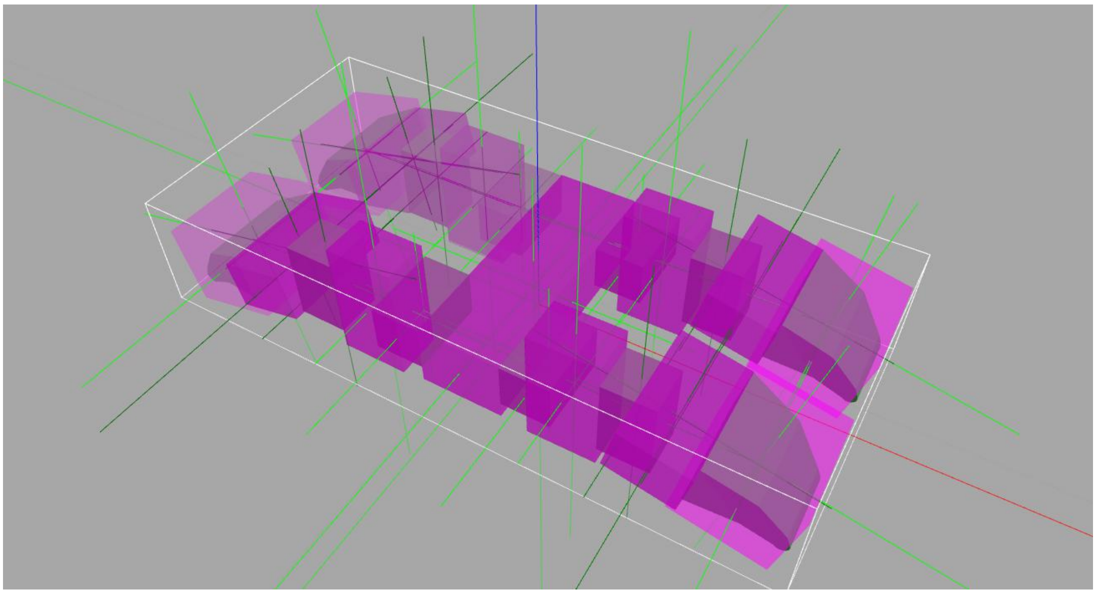

Figure 5 Rendering of the moments of inertia (as cuboids) for the ALLBOT robot model.

4. Conclusion and Outlook

It is shown that it is possible to evolve effective gaits with machine learning techniques, in this case, genetic algorithms. This is an important insight because it has several advantages over manually designed gaits. Manually designed gaits are static in a sense that they cannot be adjusted to a certain environment (e.g. obstacles or different undergrounds). They always have to be readjusted manually. On the other side, evolved gaits using genetic algorithms could be implemented in such a way that they learn on-line. This means that the robot is not stuck to a fixed gait, but can learn steadily after each step. This has the advantage that it can adjust its gait to a new surface or obstacles.

Since it took a very long time to find an adequate set of parameters and test each set over several hundreds of generations, we most certainly have not found the most efficient evolved gait. More training time and parameter adjustments should be done in future works. After this first essential step several topics would be of interest to study in more detail: Until now, the gaits are evolved in a robot simulation. These gaits could be transferred to the physical robot and be fine-tuned. The robot could be trained on different surfaces (in simulation and real life) with the goal that the robot automatically adapts its gait to overcome different obstacles. The ALLBOT comes with different foot shapes. Training the robot on these different shapes would allow to exhibit foot specific gaits. Each foot shape could be tested on different surfaces to see if some shapes are more suitable for specific surfaces. Furthermore, additional legs could be added to the robot to create for example a hexapedal (6-legged) robot.

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