

# Neuroevolution and NEAT at Evolving Neurocontrollers for Obstacle Avoidance for a Robot Arm

Andrei Darii, Marian Sorin Nistor, Stefan Pickl

## Abstract

This paper presents a comparative analysis of Neuroevolution and NEAT algorithms for evolving neural controllers capable of evading obstacles. The fitness criterion is the number of time steps a robot is able to avoid a moving obstacle that increases in speed over time. The experiments simulate the WLkata Mirobot, a small 6-joint robot, focusing on obstacle evasion using forward kinematics. The results show the average number of generations required by each algorithm to achieve a certain fitness and analyze the average fitness per generation. This comparison offers insights into the effectiveness and efficiency of each algorithm in optimising robotic obstacle avoidance.

**Keywords:** Genetic Algorithm, Neuroevolution, NEAT, Robot Arm, Obstacle Avoidance

## 1 Introduction

The development of autonomous robotic behaviour through the use of artificial neural networks (ANNs) has become a vital area of research within the fields of robotics and artificial intelligence. The ability of robots to adapt to dynamic environments, particularly in tasks such as obstacle avoidance, is critical for the safe and effective operation of such systems. Neuroevolution, a machine learning approach, has shown to perform in a competitive manner with Reinforcement Learning (RL)

methods [1, 2]. Both Neuroevolution and its more sophisticated variant, NEAT (NeuroEvolution of Augmenting Topologies), are prominent methods employed to evolve neural controllers, offering unique approaches to optimising robotic behaviour [3, 4, 5].

Neuroevolution is a method that focuses on evolving fixed-topology networks by optimising the weights of connections within the ANN. This makes it a straightforward and powerful method for a wide range of tasks. In contrast, NEAT dynamically evolves both the network topology and the connection weights, thereby enabling it to discover more complex solutions when required. The flexibility of NEAT has contributed to its success in a range of domains. However, its performance in specific tasks, such as obstacle avoidance, compared to traditional Neuroevolution, remains an open question.

The Wlkata Mirobot is a compact 6-joint portable robotic arm created for teaching and programming in robotics [6]. The arm is simulated to perform obstacle avoidance tasks using forward kinematics. The 6-axis robotic arm, illustrated in Figure 1, emulates the kinematics of larger industrial robots, making it a viable and scalable option for research and educational purposes [7].

In real-world applications, robotic arms often operate in environments where obstacles, such as other machinery (especially in collaborative robotics), humans, or unpredictable objects, may enter their designated workspace. It is crucial to ensure that the robot is able to autonomously avoid collisions in order to prevent damage to the robot itself, as well as to the surrounding equipment, and injury to humans. To take one example from the field of medical robotics, a surgical robot may need to evade sudden movements by the patient or other equipment in the operating room [8, 9].

The objective is to make real-time adjustments to avoid collisions, and the effectiveness of the neural controller directly influences the robot’s ability to evade obstacles. By comparing the performance of Neuroevolution and NEAT in this specific task, insights can be gained into which approach is better suited for evolving neural controllers that can handle dynamic, real-world scenarios.

## 2 Setup and Results

In the present experiment, the Wlkata Mirobot, a 6-joint robotic arm, was employed as a model to assess the efficacy of Neuroevolution and NEAT in obstacle avoidance. The forward kinematics of the robot are calculated using its Modified Denavit-Hartenberg parameters, as presented in Table 1, and the angle limits, as shown in Table 2. This enabled to simulate the robot's motion with great accuracy, as illustrated in Figure 2. The obstacle, represented by a sphere with a radius of 10 units, is randomly positioned in a range of 200 to 250 units from the robot's end effector. At spawn, the obstacle determines the direction towards the end effector and proceeds in that direction at a speed of 10 units per time step. This speed is increased by 0.01 units per time step until it reaches a maximum of 30 units per time step. The obstacle then moves along its trajectory for 500 units before re-spawning and recalculating its trajectory.

In the design of the neural controllers for both algorithms, the focus is on controlling the first three joints of the Wlkata Mirobot. This decision is based on the observation that the last three joints do not significantly affect the position of the robot's end effector. By limiting the control to the first three joints, the complexity of the controller is reduced while still retaining the ability to perform effective obstacle avoidance.

| $\theta$ (rad)              | $d$ (mm) | $a$ (mm) | $\alpha$ (rad)   |
|-----------------------------|----------|----------|------------------|
| $0 + \theta_1$              | 127      | 0        | 0                |
| $-\frac{\pi}{2} + \theta_2$ | 0        | 29.69    | $-\frac{\pi}{2}$ |
| $0 + \theta_3$              | 0        | 108      | 0                |
| $0 + \theta_4$              | 168.98   | 20       | $-\frac{\pi}{2}$ |
| $\frac{\pi}{2} + \theta_5$  | 0        | 0        | $\frac{\pi}{2}$  |
| $0 + \theta_6$              | -24.28   | 0        | $\frac{\pi}{2}$  |

Table 1. Modified Denavit-Hartenberg parameters for the Wlkata Mirobot

| Joint | Angl. Lim. (deg) |
|-------|------------------|
| 1     | from -100 to 160 |
| 2     | from -40 to 70   |
| 3     | from -120 to 60  |
| 4     | from -180 to 180 |
| 5     | from -205 to 35  |
| 6     | from -360 to 360 |

Table 2. Angle Limits for Each Joint of the Wlkata Mirobot

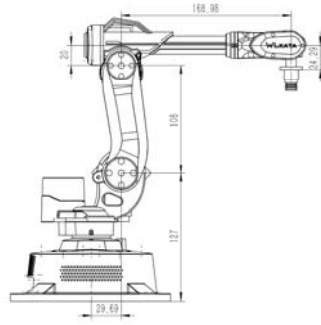


Figure 1. The size parameters of WLkata Mirobot in mm

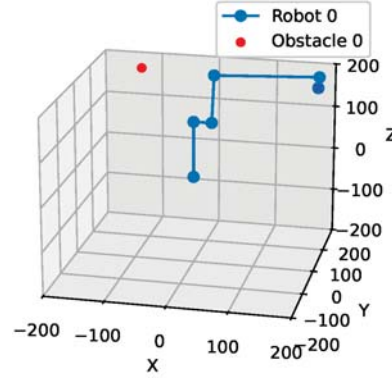


Figure 2. Forward kinematic representation of the robot along with the obstacle

Both the Neuroevolution and NEAT algorithms utilise neural controllers with 10 inputs and 3 outputs, comprising a population of 64 individuals. The inputs include the obstacle's speed, its relative and absolute positions, and the current angles of the robot's first three joints. The outputs represent the adjustments required for these joints that are in range  $[-1, +1]$  degrees, enabling the robot to react to the obstacle's movement. This leads to the following fitness function:

$$f(t) = f(t - 1) + \Delta f \quad \text{if the robot evades the obstacle at timestep } t.$$

The Neuroevolution method employs a fixed neural network topology with two hidden layers, each containing 64 nodes.

Figure 3 presents the results of a comparison between the average number of generations required to achieve a certain fitness and the average fitness per generation for both algorithms. The figure illustrates the average fitness per generation across 100 runs for both the NEAT and Neuroevolution algorithms. Both methods demonstrate a gradual increase in fitness, indicating improved obstacle avoidance over time. Initially, Neuroevolution outperforms NEAT, achieving higher fitness

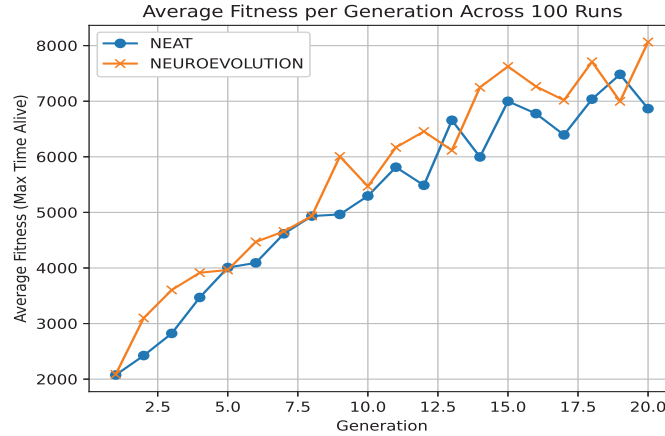


Figure 3. Average fitness per generation across 100 runs for both the NEAT and Neuroevolution algorithms is presented, with fitness defined as the maximum time alive for the robots in the obstacle avoidance task.

levels in the early generations. However, as training progresses, both algorithms converge to a similar level of performance.

The number of generations required to surpass a fitness score of 8000 which equivalates with the robot evading the obstacles for a significant amount of 8000 time-steps, is nearly identical for both methods, with NEAT averaging 11.58 generations and Neuroevolution slightly faster at 11.32 generations. Despite some fluctuations, Neuroevolution shows a sharper increase in fitness towards the end, indicating a potential advantage in later training stages.

The results demonstrate the performance of both algorithms, but the focus on only the first three joints of the robot arm limits the applicability to more complex scenarios. Furthermore, the use of a fixed, predictable obstacle does not fully capture the variability found in real-world settings. Additionally, the reliance on a specific fitness function based on the time steps a robot avoids an obstacle may overlook other potential strengths or weaknesses of the algorithms in different tasks.

### 3 Conclusion

The present study compared the performance of NEAT and Neuroevolution in evolving neural controllers for robotic obstacle avoidance. Considering the introduced limitations, both algorithms demonstrated the capacity to improve fitness over time.

Neuroevolution showed a faster initial improvement in early generations, while NEAT reached a comparable level in subsequent stages. The distinction between these algorithms lies in their approach to the task at hand. NEAT starts with a minimal neural network topology and proceeds to gradually optimise and modify it across generations. This process may result in comparatively slower initial progress in comparison to Neuroevolution, which operates on a fixed topology from the outset. However, this could potentially lead to more complex and effective solutions over extended training periods.

Further research might address the presented limitations and could also explore hybrid approaches that combine elements of both Neuroevolution and NEAT to leverage their respective strengths.

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### References

- [1] Tim Salimans, et al. *Evolution strategies as a scalable alternative to reinforcement learning*. arXiv preprint arXiv:1703.03864, 2017.
- [2] Felipe Petroski Such, et al. *Deep neuroevolution: Genetic algorithms are a competitive alternative for training deep neural networks for reinforcement learning*. arXiv preprint arXiv:1712.06567, 2017.

- [3] Thomas D'Silva and Risto Miikkulainen. *Learning dynamic obstacle avoidance for a robot arm using neuroevolution*. Neural processing letters 30, 2009, pp. 59–69.
- [4] Pei-Chi Huang, et al. *Grasping novel objects with a dexterous robotic hand through neuroevolution*. 2014 IEEE Symposium on Computational Intelligence in Control and Automation (CICA), IEEE, 2014.
- [5] Ruoshi Wen, et al. *Neuroevolution of augmenting topologies based muscilor-skeletal arm neurocontroller*. 2017 IEEE international instrumentation and measurement technology conference (I2MTC), IEEE, 2017.
- [6] Miriam Pekarcikova, et al. *Wkata educational robots used in simulation in the laboratory conditions*. Acta Simulatio 9.3, 2023.
- [7] Dongxu Zhou, Jia Ruiqing, and Xie Mingzuo. *Mirobot: A Low-Cost 6-DOF Educational Desktop Robot*. Robotics in Education: RiE 2021 12. Springer International Publishing, 2022.
- [8] J. Patalas-Maliszewska, A. Dudek, G. Pajak, I. Pajak. *Working toward Solving Safety Issues in Human-Robot Collaboration: A Case Study for Recognising Collisions Using Machine Learning Algorithms*. Electronics, 2024, vol. 13, no. 4, Article ID 731.
- [9] S. Patil, V. Vasu, K.V.S. Srinadh. *Advances and perspectives in collaborative robotics: a review of key technologies and emerging trends*. Discov Mechanical Engineering, vol. 2, Article No. 13, 2023.

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