# Comparative Analysis of Neuroevolution Algorithms: Evolving Connection Weights versus Topology in Robotics Applications

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## 1. Introduction

### 1.1 Background Information

Neuroevolution algorithms are one of the significant achievements in the field of artificial intelligence and robotics. They employ the concepts from natural selection and enhance neural networks in a way that it makes it more adaptive and responsive to variety of intelligent behaviors. These algorithms are very important for robots in object manipulation, pattern recognizing etc. The ability of these algorithm to evolve is particularly very important in real-life scenarios for the robots as the environment around is constantly changing. In these instances, traditional method of learning fails but these neuroevolutionary methods enable us to tackle them.

### 1.2 Problem Statement

Neuroevolution algorithms evolve in two distinct ways. The first method involves evolving or improving by merely adjusting the weights of neurons in a fixed network, based on the belief that this alone can deal with complex tasks. On the other hand, the second method not only alters the weights but also changes the network's topology to address complex problems. The effectiveness of these two methods compared to each other in real-world situations remains a topic of debate.

### 1.3 Purpose of the Analysis

The goal of this analysis is to systematically collect and summarize existing research on neuroevolution algorithms, focusing on those that evolve only the connection weights versus those that also modify the network topology or structure. The aim is to determine which approach shows more efficacy and potential in robotic applications, assessing their performance, adaptability, and practicality in handling complex tasks in robotics.

### 1.4 Research Questions/Hypotheses

The analysis is guided by the following research questions:

- **RQ1**: What are the neuroevolution algorithms that specifically focus on weight evolution within a fixed topology, and how have they been applied in robotics?
- **RQ2**: Which neuroevolution algorithms are capable of evolving both the network topology and weights, and what contributions have they made to advancements in robotics?
- **RQ3**: In terms of performance metrics and practical implementation, how do the two approaches compare within the field of robotics?

## 2. Methodology

This section outlines the systematic approach adopted for conducting the literature search, selection, and analysis pertinent to neuroevolution algorithms in robotics.

### 2.1 Literature Search

The literature search was conducted across several academic databases. The databases included IEEE Xplore, ScienceDirect, SpringerLink, Aston Library and the ACM Digital Library. Additional sources were identified through the references of key articles. The search terms used were combinations and variations of the following: "neuroevolution algorithms," "evolutionary neural networks," "fixed topology," "weight evolution," "topology evolution," "robotics application," and "adaptive robotics." Boolean operators (AND, OR) were utilized to refine the search.

### 2.2 Selection Criteria

The inclusion criteria were:

- Peer-reviewed articles and papers written in English.
- Studies that explicitly discussed neuroevolution algorithms applied to robotics.
- Articles that provided clear results on the performance and adaptability of the algorithms.

The exclusion criteria were:

- Non-peer-reviewed articles and grey literature.
- Papers that did not focus on neuroevolution algorithms or their application in robotics.
- Studies lacking empirical results or proper methodological descriptions.

Duplicates were removed, and an initial title and abstract screening were conducted to assess relevance.

## 3. Evolution of Connection Weights in Fixed Topologies

### 3.1 Overview

In the world of neuroevolution, a key method involves fine-tuning the signal weights in neural networks whose structure doesn't change. This simpler approach speeds up the process of finding effective solutions by not altering the network's structure. It's based on the idea that even a fixed network design can handle various tasks effectively, just by adjusting these signal strengths.

### 3.2 Key Algorithms

This approach is characterized by several algorithms. Genetic Algorithms (GAs), pioneered by Holland in 1992,Particle Swarm Optimization (PSO) and Evolution Strategies (ES)

### 3.3 Applications in Robots:

In autonomous vehicles, it aids in real-time navigation and obstacle avoidance, as evidenced in studies by M. R. C. Qazani, M. Karkoub, H. Asadi, C. P. Lim, A. W. -C. Liew, and S. Nahavandi (2022).The study focuses on using the multi-objective Non-dominated Sorting Genetic Algorithm II (NSGA-II) for tuning the weights of a nonlinear Model Predictive Controller (MPC) in AVs. The researchers employed the multi-objective NSGA-II algorithm to tune the weights of the MPC-based controller.

The method's adaptability and effectiveness are underscored by its wide range of applications in tackling various challenges in robotics.

### 3.4 Advantages and Limitations

The primary advantage of evolving weights within fixed network structure is computational efficient. With a reduced search space, algorithms can often find optimal or near-optimal weight more quickly than those that also evolve topologies. Additionally, this approach allows for greater control over the network architecture, which can be beneficial to specific tasks.

However, there are also significant limitations to this approach. A fixed topology may not be capable of expressing the range of diversity required for more complex tasks. There is also a risk of overfitting. Moreover, by not evolving the topology potentially more innovative and efficient network structures might be overlooked.

## 4. Evolution of Both Topology and Weights

### 4.1 Overview

Evolving both the network structure and connection strengths in neuroevolution offers a more diverse and potentially better method. This approach goes beyond just fine-tuning weights it also supports the creation of new network structures.

### 4.2 Key Algorithms

The most prominent algorithm in this category is NEAT (NeuroEvolution of Augmenting Topologies). Developed by Stanley and Miikkulainen (2002), NEAT starts with simple networks and gradually improves them by introducing new nodes and connections through mutations. This allows the network to grow in complexity in response to the requirements of the tasks . Other significant algorithms include HyperNEAT which was introduced as a variant for NEAT by Kenneth O. Stanley et al (2009) which allows for the evolution of large-scale neural networks.

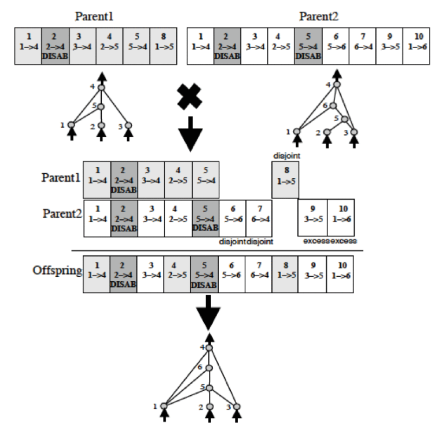


*Figure 1: Showing the Evolution of Network Topology NEAT Stanley and Miikkulainen (2002)*

### 4.3 Applications in Robotics

An extended version of HyperNEAT called ES-HyperNEAT has been used to develop control systems for legged robots P. Reyes and M. -J. Escobar 2019, allowing them to adapt their gait to different terrains. Additionally, these techniques are employed for evolving behaviors in object manipulation or adaptive interaction, as demonstrated by Jalali et al (2019) where the authors explored the application of the Evolutionary Multi-Verse Optimizer (EMVO) algorithm for autonomous robot navigation.

## 4.4 Advantages and Limitations

Adjusting both the structure and signal strengths of neural networks allows creating complex designs for specific tasks, making robots more efficient and effective. However, it's not without limitations, it requires exploring a much larger range of possibilities or it has a larger search space, which can increase the time and computing power needed. Also, these complex networks can be harder to understand and might not always adapt well to new situations or tasks.

## 5. Comparative Analysis

## 5.1 Comparative Framework

To compare the performance of neuroevolution algorithms that evolve both topology and weights with those that evolve only weights.

## 5.2 Performance Comparison

- **Fixed Topology Algorithms:** For instance, in robotic path planning, these algorithms can navigate simple environments efficiently. As was demonstrated in the work of Floreano, D. and Mondada, F., (1996). This study demonstrates the efficiency of fixed topology algorithms in structured environment. Where they evolved neural networks to control a real mobile robot.

- **Evolving Topology and Weights Algorithms**: These algorithms are more suited for complex, dynamic environments., real-time neuroevolution in the NERO video game Stanley, K.O., Bryant, B.D. & Miikkulainen, R., (2005), showcase their effectiveness in dynamic environments.

## 5.3 Practicality in Robotics

- **Fixed Topology Algorithms:** The practicality of these algorithms lies in their straightforward implementation and lower computational demands. They are well-suited for applications where the task environment is relatively stable and predictable as demonstrated in the studies conducted by Florean, D. and Mondada, F., (1996). Which highlights the application of neuroevolution algorithm to adapt robots to their environment especially fixed topology neuroevolution algorithms.

- **Evolving Topology and Weights Algorithms.:** These algorithms shine in scenarios requiring adaptability, such as search and rescue robots operating in unpredictable environments. And in the in the work of Ahmed Aly, J. Dugan (2018), where they tried to apply neuroevolution to optimize robot navigation systems in dynamic environments instead of derivative-based optimization techniques such as Stochastic Gradient Descent hence highlighting the efficiency neuroevolution algorithms .

## 5.4 Innovations and Developments

Recent advances in neuroevolution have brought about multi-objective methods for predicting paths in self-driving cars. A notable study by Qazani et al (2022) utilized the Non-dominated Sorting Genetic Algorithm II (NSGA-II), initially developed by Deb et al (2002), to fine-tune the weights of a linear model predictive controller (MPC) in autonomous vehicles for achieve a balance between energy usage and motion comfort for autonomous vehicle users. Further the work of J. D. Schaffer (2020) shows how the evolution of the symmetry of the network topology can affect robotic sensory-motor decision. These are some of the new innovations being made to discover more utilization of neuroevolution algorithm in solving complex computational problems.

## 6. Discussion

## 6.1 Summary of Findings

The literature analysis on neuroevolution algorithms in robotics revealed two distinct approaches: evolving only the weights within a fixed network topology and evolving both the topology and weights. Key findings include:

- **Fixed Topology Approach**:

- **Evolving Topology and Weights**: In robotics applications, evolving both topology and weights has practically better adaptability and potential, particularly in dynamic and unpredictable environments.

## 6.2 Theoretical and Practical Implications

The comparison highlights the importance of structural flexibility in neural network design for adaptive behaviors in robotics. Practically, it suggests that for complex, real-world applications in robotics, algorithms that evolve both topology and weights might be more suitable despite their higher computational demand.

## 7. Conclusion

The main findings from this comparative analysis are as follows:

1. **Fixed Topology Approach**: This method, while demanding less computation power and is faster in converging to the optimal solution, can be limited by its limitation of not being able to change the structure of the fixed structure according to the demands of the task. It works well for specific, well-defined problems but lacks the flexibility needed for more dynamic environments.

2. **Evolving Topology and Weights**: This approach, employed by algorithms like NEAT Stanley, K.O. and Miikkulainen, R (2002) offers greater adaptability and potential for innovation in network structure. It is however more demanding when it comes to computation power but it can evolve more complex and efficient solutions suitable for more broad and continuously changing problems.

The conclusion drawn from this analysis is that while both approaches have their benefits, the evolving topology and weights approach holds more potential for complex and dynamic tasks in robotics. This approach aligns with the current trends in robotics that demand high adaptability, precision, and efficiency. As we are progressing into the future, where robots are designed to handle really complex tasks.

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