A Review on NEAT and Other Reinforcement Algorithms in Robotics

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Abstract: Artificial neural networks, or ANNs, find widespread use in real-world scenarios ranging from pattern recognition to robotics control. Choosing an architecture (which includes a model for the neurons) and a learning algorithm are important decisions when building a neural network for a particular purpose. An automated method for resolving these issues is provided by evolutionary search techniques.Genetic algorithms are used to artificially evolve neural networks in a process known as neuroevolution (NE), which has shown great promise in solving challenging reinforcement learning problems. This study offers a thorough review of the state-of-the-art techniques for evolving artificial neural networks (ANNs), with a focus on optimizing their performance-enhancing capabilities.

Key Words: Artificial neural networks,Neuroevolution, NeuroEvolution of Augmenting Topologies,Brain computer interface.

1.INTRODUCTION

Over the past five decades, scholars across various disciplines have employed models of biological neural networks not only to gain deeper insights into the functioning of biological nervous systems but also to develop robust tools for engineering purposes.

Artificial neural networks (ANNs) are computational models, implemented either in software or specialized hardware, designed to emulate the behavioral and adaptive characteristics of biological nervous systems. Typically, ANNs consist of interconnected processing units, often referred to as "neurons," which can receive multiple inputs and produce outputs. Conceptually, an ANN can be represented as a directed graph, where each node corresponds to a neuron model. At its simplest, a neuron model involves calculating a weighted sum of incoming signals, which is then transformed by a non-linear transfer function. However, more advanced neuron models may incorporate discrete-time or continuous-time dynamics. The connections between neurons, represented as edges in the graph, are characterized by synaptic weights. Neurons that interact directly with the external environment are commonly known as input or output neurons [Fig. 1]. The architecture, or topology, of a neural network is defined by the arrangement of neurons and the possible connections between them.

Neuroevolution is a field within artificial intelligence that employs evolutionary algorithms to gradually evolve neural networks. This approach has the potential to automate the neural network design process, streamlining the creation and optimization of these complex systems. A groundbreaking NeuroEvolution technique known as NeuroEvolution of Augmenting Topologies (NEAT) has been developed with the aim of enhancing architecture optimization by reducing the dimensionality of the search space for connection weights. NEAT achieves this by gradually expanding network topologies from their minimal forms, ultimately identifying the optimal topology with the smallest possible dimensional space. This innovative approach results in notable improvements in both training speed and accuracy. The idea of evolving topologies and parameters was then extended to automate the design of a neural network's topology. This would save human efforts and possibly generate a more effective network.

2. NeuroEvolution of Augmenting Topologies (NEAT)

NEAT's genetic encoding scheme is designed to facilitate the alignment of corresponding genes during mating when two genomes cross over. Genomes are represented linearly and consist of connection genes [Fig. 2], each connecting two node genes. Node genes define inputs, hidden nodes, and outputs available for connection. Each connection gene specifies the input and output nodes, the connection weight, whether it's enabled, and an innovation number for identifying corresponding genes. Crossover is a fundamental genetic operator in NEAT that promotes genetic diversity by combining beneficial traits from different individuals. By recombining genetic material, NEAT explores new regions of the solution space, facilitating the evolution of increasingly effective neural network architectures for the given task.Mutation in NEAT can change both connection weights and network structures. Through mutation, the genomes in NEAT will gradually get larger. Mutations can happen in a variety of ways. The discussion in [1] is centered on making the search space less complex. Reducing the crossover rate in the algorithm facilitates learning. This is because less gene interchange ensures that valuable genetic patterns are not fragmented or lost during chromosome mating. By adjusting the crossover parameter and making minor modifications, it has been demonstrated that the performance of NEAT can be enhanced. This allows the NEAT algorithm to evolve gradually while preserving information, even during complexification. Consequently, the learning process in NEAT is significantly improved compared to conventional evolutionary methods.

3. Robotics

NEAT (NeuroEvolution of Augmenting Topologies) has been widely applied in the realm of robotics, notably contributing to the advancement of adaptive and intelligent control systems. A new AI agent that trains robots has been unveiled by Nvidia Corporation. In order to assist robots in learning more sophisticated skills, the agent [2] makes use of GPT-4's natural language capabilities in conjunction with reinforcement learning. Reinforcement learning has enabled impressive wins over the last decade, yet many challenges still exist, such as reward design, which remains a trial-and-error process. In [3], a pioneering controller design for autonomous quadrotor flight is introduced, employing an evolutionary neural network. The main goal of this controller is to guide the quadcopter to a specified position, considering flight constraints and target destinations. Developed as a single multi-layer perceptron, the neuro controller regulates rotor speeds based on the quadcopter's present state. Training entails a tailored evolutionary algorithm, with a key focus on defining a suitable cost function. Simulation results demonstrate the neuro controller's ability to navigate the quadcopter through complex trajectories with precision and minimal travel times, highlighting its effectiveness in managing autonomous flight tasks. [4] presents an optimal trajectory design for a single drone to ferry data from a temporary base station. The main advantage is that you can apply the genetic algorithm to solve drone trajectory optimization problems for post-disaster communication.Investigating the interaction between human investors and robo-advisors, the research examines how NEAT-based algorithms are utilized and the consequent impact on investment performance[5].It reveals that investors encountering higher default rates in their manual investing practices exhibit a reluctance to adopt NEAT-powered robo-advisors, contrary to initial expectations. [6] explores the profound implications of this concept within the trajectory of computerization, particularly regarding the displacement of human labor by machines. The paper underscores the pivotal role of NEAT and similar AI approaches in bridging the gap between human tacit knowledge and machine intelligence, ultimately reshaping the future of labor and technology integration.

4. Brain Computer Interface

NEAT offers a flexible and adaptive framework for developing Brain computer interface (BCI) that can translate neural signals into actionable commands or control signals. By evolving neural network architectures, NEAT-based BCIs can provide intuitive and personalized interfaces for individuals to interact with the external world using their thoughts or intentions. [7] Explains the importance of BCI. BCI is one such emerging technology in Neurosciences. In a nutshell, BCI technology provides direct communication between the brain and an external device, bypassing the normal neuromuscular pathways. BCI not only serves the medical field & health care but also has a role in various other arenas of human life like entertainment, gaming, education, self-control, marketing, and so on. In [8], it delves into the opportunities and challenges of incorporating brain science into AI, highlighting the potential for significant advancements in AI research through a deeper understanding of the brain's mechanisms and functions. The evolution of AI, notably marked by breakthroughs like deep learning, owes much to insights from brain science. Despite significant progress, a gap remains between AI and human intelligence. Bridging brain science with AI research is crucial for deeper understanding and improving AI capabilities. Integration promises insights into intelligence and advancements in AI systems.

5. Gaming

NEAT provides a robust framework for game development,enabling creators to craft adaptive, intelligent, and immersive gaming experiences across diverse genres and platforms. Utilizing NEAT, game developers can foster innovation and elevate gameplay mechanics, content generation, and AI-driven features. In [9], NEAT uses a genetic algorithm with clustering based on gameplay logs to evolve agents with diverse playstyles in a gaming environment. Using NEAT, it has potential for dependent learning, optimization, and automation. Although limited human interaction, ethical concerns, and unpredictable behavior are major concerns,. [10] Employing the NEAT algorithm for evolving artificial neural networks through a genetic algorithm to play Flappy Bird. It builds a most optimal network by itself by adding nodes or connections, or changing the weights of the connections. NEAT-based AI revolutionizes the capabilities of non-player characters (NPCs) in games, elevating their realism and adaptability to unprecedented levels. Through evolved neural networks, NPCs showcase intricate behaviors, including decision-making, navigation, social interactions, and learning from player interactions. This leads to immersive and dynamic gameplay experiences, enriching players' encounters with challenges and opportunities for engaging interactions within the game world.

5. Figures and Tables

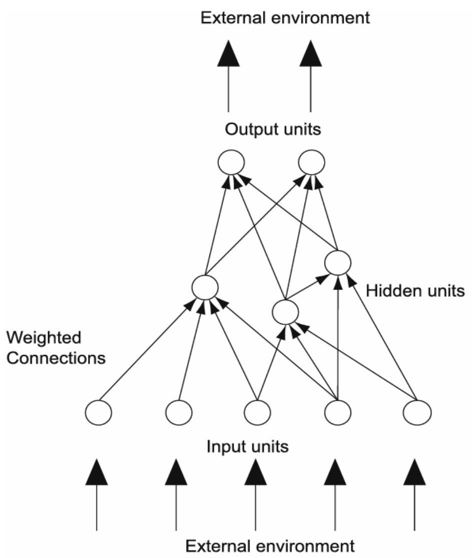

Fig. -1:A generic neural network architecture.

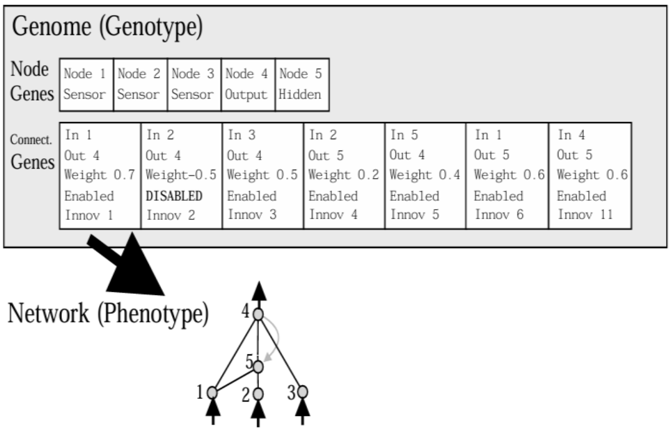

Fig. -2: Neat Encoding.

6. CONCLUSIONS

This paper mainly focuses on applying NEAT in three fields: robotics, brain-computer interfaces, and gaming. NEAT can make significant impacts in these areas. Additionally, the main drawbacks of NEAT are discussed here. The NEAT algorithm, with slight modifications, can be enhanced to better apply in real-world applications. The paper delves into the potential benefits of NEAT in each field, highlighting its adaptability, efficiency, and potential for optimization. It also explores the challenges faced in implementing NEAT in practical scenarios, such as scalability issues, computational complexity, and the need for extensive parameter tuning. The paper proposes modifications to the NEAT algorithm to address these challenges and improve its applicability in real-world settings. These enhancements may include adjusting the mutation rates, introducing new genetic operators, or integrating additional mechanisms for diversity maintenance and exploration-exploitation balance. The paper provides insights into the potential of NEAT in various domains and offers suggestions for overcoming its limitations to unleash its full potential in practical applications.

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