Robot Evolution for Autonomous Behavior in Dynamic Environments

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December 16, 2023

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November 2023

Abstract

This paper introduces a novel robot parallel evolution design algorithm, leveraging the concept of a module network, to optimize the learning process of collision avoidance, approach, and wall switching behaviors in evolutionary robots. The proposed algorithm is validated and tested, demonstrating its efficacy in enabling evolutionary robots to autonomously exhibit behaviors such as collision avoidance, movement, replication, and attack.

The learning methodology focuses on refining the neural network-based strategies for collision avoidance, approach, and wall switching behaviors. The evolutionary robots, operating in a simulated environment, showcase the ability to adapt and enhance their performance over time. The simulation environment includes randomly generated rectangular obstacles with varying side lengths, strategically placed to represent real-world challenges. Additionally, the environment features randomly scattered approach targets, serving as goals for the robots.

The modular design of the neural network allows for the integration of fundamental behaviors such as collision avoidance and approach, enabling a progressive enhancement of the robot's capabilities. As the neural network evolves, the robots demonstrate an increasingly sophisticated ability to navigate their surroundings, avoid obstacles, approach targets, and adapt to dynamic scenarios.

Through extensive simulations, the proposed algorithm proves effective in training evolutionary robots to navigate complex environments autonomously. The study contributes to the field of evolutionary robotics by presenting a modular neural network approach that enables the gradual acquisition and integration of diverse behaviors, showcasing the potential for autonomous and adaptive robotic systems in dynamic and challenging environments.

1 Introduction

In the realm of robotics, traditional design methods have historically relied on a structured environment with precise prior knowledge of both the robot and its operational surroundings. However, this conventional approach presents significant challenges, particularly in terms of the constant need for modifications as knowledge about the robot and its environment evolves. The intricate process of establishing mathematical models for both the robot and its surroundings has imposed an overwhelming workload on engineering implementations.

Recognizing the limitations of this traditional paradigm, recent research has shifted its focus towards enhancing robot adaptability. Departing from the conventional "top-down" approach rooted in symbolic reasoning, contemporary methodologies explore a "bottom-up" strategy inspired by biological evolution. This novel perspective emphasizes perception, action, and learning through interaction with the environment.

This thesis delves into the pivotal question of how to implement behaviorism in the design of intelligent robots, emphasizing the importance of learning behavioral actions through interaction with the environment. The cornerstone of this approach lies in reinforcement learning, which treats the learning process as heuristic evaluation. The robot selects actions, acts on the environment, and receives feedback in the form of reinforcement signals, guiding subsequent actions based on the current state and the environment.

In this pursuit, the thesis explores the integration of evolutionary neural networks into the robot behavior model. The research process deliberately avoids the necessity for complete environmental knowledge, allowing robots to operate seamlessly in entirely unknown environments.

To overcome the challenges posed by a lack of environmental and self-knowledge, formal methods are employed, enabling developers to test robots and their interactions in simulated and stable environments. The robot's environment model is constructed based on its own perception, facilitating self-recovery and continual learning. Learning, in this context, refers to the robot's ability to update knowledge through experimentation, observation, and speculation, ensuring continuous improvement in adaptability.

The primary achievements outlined in this paper include the proposal of an artificial neural network structure parallel evolution design algorithm, focusing on module networks. The research explores the learning methods and models for robot behaviors such as collision avoidance, approach, and wall switching. The thesis also presents a multi-robot formation control algorithm, showcasing the integration of advanced combinational behaviors realized through evolutionary neural networks.

Addressing challenges in network structure design, the paper introduces a novel algorithm that decomposes complex problems into simpler ones, leveraging a parallel genetic algorithm to enhance efficiency. Experimental results indicate that this combination significantly improves convergence speed and solution quality, marking a paradigm shift in the autonomous learning capabilities of robots.[5][3][4][2][1]

2 Genetic Algorithms and Hierarchical Parallel Processing for Neural Network Optimization in Complex Problem Solving

2.1 Neural Networks and Generalization

Issue Lack of generalization ability and interference phenomena in neural networks. **Cause** Too many degrees of freedom in the network structure. Solution Approach: Use efficient learning algorithms and network structures. A divide-and-conquer strategy is proposed to decompose complex problems into simpler sub problems.

2.2 Genetic Algorithms and Parallel Processing

Application Genetic algorithms used to solve large-scale optimization problems. **Challenge** Increased operation time for large and complex problems. **Solution** Proposes a parallel genetic algorithm to reduce operation time while improving solution quality.

2.3 Simulation of Brain Growth Using Genetic Algorithm

Objective Simulate the growth process of the brain and mimic biological nervous system characteristics. **Approach** Use genetic algorithms to establish a genetic search and artificial growth model. Decompose complex problems, introduce processing units at different levels, and employ multi-slave processing units to enhance pattern searching efficiency.

2.4 Simulation of Plant Growth Using Fractals and Genetic Algorithms

Model Simulating plant growth using a parallel string rewriting mechanism based on fractals. **Constraint Rules** Introduce modular structure constraint and self-similar constraint. **Genetic Algorithm** Generate initial bit strings using genetic algorithms. The algorithm's parameters impact solution quality.

2.5 Hierarchical Parallel Algorithm

Steps Problem decomposition, coding, initialization, chromosome grouping, task assignment, and iterative operation. **Feature** Introduction of auxiliary processing units to form a hierarchical communication topology, enhancing processing unit capacity.

2.6 Adaptive Robotics Design

Traditional Approach Problems with prior knowledge requirements for robot and environment. **New Approach** Focus on robot adaptability in unknown environments. Emphasizes learning through continuous interaction with the environment. **Learning Mechanism** Robots update knowledge through experimentation, observation, and speculation.

2.7 Evolutionary Robot Model

Approach Bottom-up design inspired by biological evolution, emphasizing perception, action, and learning in interaction with the environment. **Behavior Control** Neural network controls robot behavior and behavior switching. **Genetic Algorithm** Used for encoding and evolving each module, akin to the process of robot reinforcement learning.

2.8 Simulation Results: Outcome

Simulation experiments prove the effectiveness of the proposed methods in various applications, including optimization and robotic adaptability. The text covers a range of topics, from addressing challenges in neural network design to the application of genetic algorithms in optimization and robotics, with a focus on adaptability and learning in unknown environments.

3 Evolutionary Robotics, Integrating Collision Avoidance and Target Approach Behaviors in Complex Environments

describe the setup and parameters of a simulation environment for studying the behavior of a robot. Let's break down and explain some
key points

Environment Description

The simulation environment is a square region with obstacles represented by randomly generated rectangular regions. The maximum number of obstacles is denoted as 'a.' The simulation progresses with increasing complexity, incorporating collision avoidance, approach behavior, and combined behavior scenarios. The robot always starts from the same point, with its initial direction randomly selected.
Obstacles and Targets

Obstacles are rectangular regions with randomly generated sizes. Approach targets are circular symbols randomly scattered in the environment. Acquiring a target is represented by the robot reaching the target's center, triggering the target's disappearance. For combined behavior, successful target acquisition results in a positive score, while collisions lead to a negative score.

Robot Model

The robot model consists of points representing the robot's center, the end of the tactile sensor, and two points for the target approach sensor. Tactile sensors are divided into front and rear sensors, with a specific angle relative to the front and rear axes of the robot. The approach sensor's distance and range are controlled by genetics. The approach sensor input is low resolution, and the relative strength of the signals is used rather than absolute strength.

Behavior Control and Motor Output

Behavior control is implemented using a modular neural network structure. The network consists of multiple modules, each with input nodes, a hidden layer, and an output node. Weights of neural networks are encoded with bits. Motor outputs control the robot's movement, with different speeds (backward, stop, forward, fast forward) for each track.

Collision Avoidance Behavior

In collision avoidance, the robot can pass through obstacles but is not allowed to cross the environmental boundary. Tactile sensing signals from the robot are used as input bits for the behavior control network. When an obstacle is detected, the robot's natural response is to turn around and move in the opposite direction.

Evolutionary Algorithm

The evolutionary algorithm involves encoding weights with bits and using a modular structure. The algorithm uses single-point crossover and a special bit-flipping variation mode. The simulation includes a fitness evaluation based on a balance between collision penalties and successful behavior.

Simulation Parameters

The simulation includes a specified number of steps for each generation. A collision penalty weight factor is introduced to balance performance. The simulation is run for a set number of generations, with observed limitations in performance improvement beyond a certain point. The environment with more obstacles takes longer to evolve.

Cross-Mapping Method

A direct mapping from tactile sensing input to motor output was attempted but found to be ineffective. There's an indication that the robot's response to obstacle detection required a more sophisticated control strategy. Overall, a detailed simulation setup, genetic encoding, and evolutionary process for developing a robot's behavior in various scenarios, including collision avoidance and target approach.

4 Evolutionary Optimization of Proximity Sensors for Adaptive Robotics in Dynamic Environments

to describe a research study or experiment related to the evolution of robot behavior using proximity and tactile sensors. Let me break down the key points:

4.1 Proximity Sensor vs. Tactile Sensor

The proximity sensor's input is based on the difference between left and right sensing signals. Chromosomes of bits are used, with added bits encoding sensor parameters like detection range and distance between sensor endings.

4.2 Environmental Adaptation

The sensor parameters evolve differently based on the environment. In a single-target source environment, the proximity sensor has larger spacing and detection range, while in a multiple-target source environment, it has smaller spacing and detection range. The adaptation process affects convergence time, with lower-performing robots remaining in the group longer before being replaced.

4.3 Switching Mechanism

A switching mechanism is proposed where collision avoidance behavior is activated when the tactile sensor detects an obstacle, and approach behavior is activated when the proximity sensor is in free space.

4.4 Simulation Environment

The simulation involves variable obstacle positions, sizes, and shapes, with a constant number of obstacles and target sources. The robot design remains mostly consistent, with fixed parameters for the approach sensor. The study compares average fitness values in different simulation environments.

4.5 Learning Curve and Adaptability

The learning curve indicates a steeper improvement in robot performance, attributed to the reduction in the number of behavior outputs. Continuous learning is emphasized for improving adaptability, and the study focuses on the robot's ability to learn by interacting with its environment.

4.6 Behaviorism and Neural Networks

Suggests a bottom-up approach to designing intelligent robots based on biological evolution and sensory interaction with the environment. Integration and switching of multiple basic behaviors are studied, with a neural network controlling behavior and behavior switching.

4.7 Clock Mechanism for Behavior Change

An internal state clock is introduced to improve the distribution of robot behavior. The clock is encoded in bit-binary, influencing the activation of basic behaviors based on the robot's movement towards its goal.

4.8 Evolutionary Robot and Neural Network

The importance of evolutionary robotics as a significant branch in the field, emphasizing the simplicity and autonomy of the structure. Neural networks, especially evolutionary neural networks, are seen as promising for robot research and development. It seems like this is part of a detailed research paper or report on the experimental evolution of robot behavior in different environments using a combination of proximity and tactile sensors. The study explores the adaptability of robots through learning and the effectiveness of different behavioral switching mechanisms.

5 Conclusion

In conclusion, this paper presents a novel approach to enhancing the adaptability and autonomous learning capabilities of robots through the integration of artificial neural networks and evolutionary algorithms. The proposed artificial neural network structure design algorithm, combined with parallel genetic algorithms, simulates the process of natural evolution and growth learning. This simulation not only effectively improves the performance and convergence speed of network structure design but also enables robots to autonomously learn complex behaviors such as obstacle avoidance, target approach, and formation keeping.

A key innovation in this work is the introduction of a modular neural network, which simplifies genetic coding, enhances network performance, and facilitates the implementation of multi-robot formation control algorithms. The research demonstrates that the evolved neural network, coupled with basic behaviors like collision avoidance and approach, enables robots to plan paths, avoid dangers, and maintain formations simultaneously. The effectiveness of the proposed algorithm is validated through simulation experiments, showcasing its performance across various formation behavior types and simulation environments.

Furthermore, the introduction of a growth neural network system overcomes inherent shortcomings in traditional evolutionary networks during the replication process. The system achieves quasi-uniform convergence over extended periods of gradual enhancement. The paper emphasizes a departure from traditional methods, focusing on the adaptability of robots without requiring complete environmental knowledge. By allowing robots to operate in unknown environments and continuously interact to obtain knowledge, the proposed approach enhances adaptability through repeated adjustments of both environmental and self-models.

The study acknowledges that these efforts represent a preliminary step and outlines future research directions, including the incorporation of analog visual functions for advanced collision avoidance, the implementation of short-term memory for recording historical states, and the joint evolution of robots based on past and current experiences. Additionally, the exploration of advanced robot behaviors such as "active visual perception" and "attention" is highlighted, suggesting the integration of behavior-based and traditional methods for a hybrid computation approach to robot visual navigation. Overall, this research lays a foundation for future developments in the field of autonomous robotic systems.

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