DOI https://doi.org/10.30525/978-9934-26-459-7-13

RESEARCH AND SYNTHESIS OF A COMPUTERIZED CONTROL SYSTEM FOR MOVING OBJECTS

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Abstract

The advancement of computerized systems for controlling moving objects such as drones, autonomous vehicles, and robotic systems presents significant technological and operational challenges. This research focuses on developing an integrated control system that utilizes real-time data processing, machine learning algorithms, and networked communication to enhance the autonomy and efficiency of moving objects. The proposed system aims to optimize route planning, object avoidance, and task execution in dynamically changing environments.

Key words: *Computerized Control, Autonomous Systems, Real-time Data Processing, Machine Learning, Networked Communication.*

Introduction

In recent years, the rapid advancement of autonomous technologies has fundamentally transformed industries ranging from logistics and transportation to urban management and defense. The core of these transformations lies in the ability to efficiently and safely control moving objects – be it unmanned aerial vehicles (UAVs), autonomous vehicles, or robotic systems – in dynamically changing environments. The traditional control systems, largely manual or semi-automated, are increasingly proving inadequate in handling the complex decision-making required for high autonomy and real-time responsiveness. This necessitates a shift towards more sophisticated, integrated control systems that leverage advancements in computation, artificial intelligence, and communications technologies.

Overview

A specific technical solution highlighted in these theses is the application of deep reinforcement learning (DRL) for autonomous drone navigation in urban environments. This method involves training a neural network to make navigational decisions by interacting with a simulated environment in a trial-and-error learning process. The network learns to maximize certain outcomes based on the rewards it receives for successful actions.

To provide a comparative analysis of the Deep Reinforcement Learning (DRL) method for autonomous navigation against other prevalent methods, it is essential to consider several key dimensions such as adaptability, computational efficiency, and the ability to handle complex dynamic environments. Here, we'll compare DRL with two other popular methods: Rule-Based Systems and Supervised Learning Models.

1. Rule-Based Systems

Description: Rule-Based Systems operate based on predefined rules and conditions that dictate the behavior of the system. These rules are often designed based on expert knowledge and are straightforward in their implementation.

Advantages:

- **Simplicity**: Easy to understand and implement. The rules are explicit, making the system's decisions transparent and predictable.
- **Deterministic**: Provides consistent outputs for known situations, ensuring reliable operation under predefined conditions.

Disadvantages:

- **Limited Flexibility**: Struggles with novel scenarios not covered by existing rules. Adapting to new conditions requires manual updates to the rule set.
- **Scalability**: Managing and updating a large set of complex rules becomes cumbersome as the operational environment grows in complexity.

2. Supervised Learning Models

Description: Supervised Learning involves training a model on a labeled dataset, where the input data is mapped to known outputs. The model learns to predict the output from the input data.

Advantages:

- **Accuracy**: With sufficient training data, supervised learning can achieve high accuracy for tasks where the relationship between input and output is well-defined and stable.
- **Generalization**: Good at handling variations within the scope of the training data. It can generalize to new data that resemble the training set.

Disadvantages:

- **Dependency on Labeled Data**: Requires a large amount of labeled data for training, which can be expensive and time-consuming to obtain.

- **Poor Adaptation to New Scenarios**: May perform poorly in situations that deviate significantly from the training data. Adapting to new scenarios often requires retraining with new data.

3. Deep Reinforcement Learning (DRL)

Description: DRL allows agents to learn optimal behaviors through trial-and-error interactions with a dynamic environment, using a reward system to reinforce good behaviors.

Advantages:

- **Adaptability**: Excellently handles dynamic and uncertain environments by continually learning from interactions, making it suitable for complex scenarios like urban drone navigation.
- **Continuous Learning**: The ability to learn continuously from ongoing interactions allows the model to improve over time and adapt to changes in the environment.

Disadvantages:

- **Computational Intensity**: Requires significant computational resources for training, especially in environments with large state and action spaces.
- **Convergence Issues**: Training can be unstable or slow, and finding the optimal policy can be challenging without careful tuning of the reward structure and learning parameters.

Comparative Analysis

- **Flexibility and Adaptability**: DRL outperforms Rule-Based Systems in adaptability and flexibility, as it does not rely on predefined rules and can adapt to new scenarios over time. While Supervised Learning models generalize well within the scope of their training data, they lack the continuous adaptability that DRL offers.
- **Operational Efficiency**: Rule-Based Systems are highly efficient during operation as they do not require real-time computation beyond rule evaluation. In contrast, both DRL and Supervised Learning require significant computational resources, with DRL often requiring more due to its ongoing learning process during operation.
- **Robustness in Dynamic Environments**: DRL is inherently designed for dynamic environments and can handle complexities that are challenging for Rule-Based and Supervised Learning models, which both require modifications or retraining to adapt to new changes.

Conclusions

This overview and the detailed discussion of a specific technical solution demonstrate the potential of the proposed computerized control system to enhance the autonomy, efficiency, and safety of moving objects. The integration of edge computing and deep reinforcement learning into the system architecture not only addresses the immediate challenges of autonomous navigation but also sets a scalable model for broader applications in various domains.

This detailed overview provides a comprehensive understanding of the system's architecture, its components, and the innovative application of deep reinforcement learning, positioning the research at the forefront of technological advancements in automated control systems for moving objects.

In conclusion, while each method has its strengths and weaknesses, DRL offers a promising approach for scenarios requiring high levels of autonomy and adaptability, despite its higher computational demands and complexity. This makes it particularly suitable for applications such as autonomous drone navigation in unpredictable urban environments.

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