Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 17, No. 1, 2025

Intelligent Robot Control and Uncertainty Analysis Integrating Reinforcement Learning and Large Language Models

Yao Zhang

Faculty of Information Technology, Monash University, Clayton VIC 3800, Melbourne, Australia

Abstract: With the rapid development of technology, the field of intelligent robot control is undergoing profound changes. The integration of reinforcement learning and big language models has brought new opportunities to enhance the intelligence level of robots. This article deeply analyzes the application of this fusion technology in robot intelligent control, explores its significance from the perspective of management, comprehensively analyzes the uncertainty of the fusion system, and proposes corresponding management strategies, aiming to provide decision-making references for managers in related fields and promote the efficient and stable development of robot intelligent control technology in practical applications.

Keywords: Reinforcement learning; Large Language Model (LLM) Intelligent control of robots; Uncertainty analysis; Management Strategy.

1. Introduction

In today's intelligent era, robots have been widely used in many fields such as industrial production, logistics and distribution, medical services, etc. The level of intelligent control of robots directly affects their task execution efficiency and effectiveness. Traditional robot control methods often exhibit insufficient adaptability when facing complex and changing environments. Reinforcement learning enables robots to learn optimal strategies through interaction with the environment, while large language models have strong language understanding and generation capabilities. The integration of the two is expected to significantly improve the intelligent control performance of robots. From a management perspective, understanding and effectively applying this integrated technology is of great significance for optimizing enterprise production processes, improving resource utilization efficiency, and reducing operating costs. [1] However, there is uncertainty in the practical application of this fusion technology, and how to identify, evaluate, and manage these uncertainties has become a key issue that managers urgently need to solve.

2. The technical principle of integrating reinforcement learning with large language models

2.1. Basic Principles of Reinforcement Learning

Reinforcement learning is a learning paradigm based on environmental feedback. In this paradigm, robots (intelligent agents) are in a specific environment, and the environmental state is described by the state space. Reinforcement learning, as an important machine learning paradigm, has achieved certain results in the field of robot control by interacting with the environment through agents and learning optimal strategies based on reward signals feedback from the environment. For example, in tasks such as autonomous navigation, grasping operations, and motion control of robots, reinforcement learning can enable robots to gradually learn to take optimal actions in different environments through continuous trial and error. [2] However, traditional reinforcement learning has problems such as low learning efficiency, high sample complexity, and dependence on environmental models when dealing with complex tasks and large-scale state spaces.

2.2. Basic Principles of Large Language Models

The big language model is based on the Transformer architecture and pre trained on large-scale text data. Taking GPT-4 as an example, in the pre training stage, the model learns language structure and semantic knowledge through tasks such as masking language models. In the masked language model task, the model randomly replaces some words in the input text with masked labels, and then predicts these masked words to learn semantic relationships and contextual information between words. After pre training, the model is fine tuned using a small amount of labeled data to adapt to specific downstream tasks. The big language model can understand the semantics of input text, generate coherent text, and also has certain knowledge reasoning abilities, such as answering complex questions and generating articles based on prompts. [3]

2.3. Implementation of Fusion Technology

In robot intelligent control systems, reinforcement learning and large language models are integrated through various methods. The big language model can generate task execution plans for reinforcement learning based on natural language task descriptions. When the user requests the robot to "find the red file in the office and deliver it to the conference room", the big language model understands the task and generates steps such as "first search for the red file in the office file cabinet, identify the file features and locate them; after finding it, plan the path to the conference room, avoid obstacles; finally place the file in the designated location in the conference room", providing task guidance for reinforcement learning.[4] The big language model can also optimize the reward function of reinforcement learning based on task understanding, human preferences, and environmental information. In the task of serving customers with service robots, the big language model analyzes customer feedback, such as "the waiter has a good attitude and serves food quickly", adjusts the reward function, and gives positive rewards to the robot for quickly and accurately serving food and using polite language, and negative rewards for delayed serving or poor attitude, guiding the robot to learn better service strategies. The reinforcement learning module provides feedback on environmental status, actions, and reward information to the big language model, which adjusts task planning and reward functions accordingly. The two work together to enhance the robot's intelligent control capabilities.[5]

3. Multidimensional analysis of uncertainty

3.1. Uncertainty at the Data Level

Data is the cornerstone of intelligent robot control. However, in practical applications, the quality and characteristics of training data are often full of uncertainty, which brings many challenges to the learning and decision-making of robots.

One common issue is the incompleteness of training data. Due to various limitations, it is difficult to cover all scenarios and situations that robots may encounter when collecting data. When training robots for home services, it may not cover all aspects such as furniture layout, item placement, and behavior habits of family members. This may result in robots being unable to make accurate decisions when faced with new scenarios that are not present in the training data. If the training data does not include furniture of a certain special shape, when the robot encounters the furniture during actual cleaning, it may collide or fail to effectively clean the surrounding area. [6]

Noise is also a key factor affecting data quality. During the data collection process, sensors inevitably introduce noise, which may interfere with the robot's accurate perception of environmental information. The images captured by the camera may be affected by factors such as changes in lighting and occlusion, resulting in noise that can cause deviations in the robot's recognition of the target object; Lidar may also experience measurement errors due to external interference when measuring distance. These noisy data entering the training process can cause the model to learn incorrect patterns, thereby reducing the performance of the robot in practical applications. [7]

The changes in data distribution will also have an impact on the intelligent control of robots. With the passage of time and environmental changes, the data distribution faced by robots may differ from the distribution of training data. In different seasons or time periods, the lighting conditions and personnel activity patterns in the home environment may change, which makes the strategies learned by robots based on fixed training data no longer applicable to new data distributions. If the robot learns a cleaning strategy under certain lighting conditions during summer training, there may be instances of cleaning omissions or excessive cleaning in certain areas after the lighting conditions change in winter. The uncertainty at the data level poses fundamental challenges to the intelligent control of robots. Overcoming these problems and improving data quality and adaptability are key steps in enhancing robot performance. [8]

3.2. Model level uncertainty

While big language models and reinforcement learning models provide powerful support for intelligent robot control, they also have some uncertainties that affect the accuracy and stability of robot decision-making.

The illusion problem of large language models has attracted much attention. The so-called illusion refers to the text generated by the model containing content that does not match the facts or is unreasonable in a given context. When a large language model is used to parse natural language instructions, if there is an illusion problem, it may pass incorrect instruction information to the reinforcement learning module, causing the robot to perform the wrong task. In the process of instruction parsing, the big language model may fabricate some non-existent task requirements or misunderstand the true intention of instructions, causing the robot to deviate from the correct direction when executing tasks. For example, misinterpreting the instruction 'bring the red cup from the living room to the kitchen' as' bring the red vase from the living room to the kitchen ', when in reality there is no red vase in the living room, can result in the robot wasting time and resources while searching for a target, and even being unable to complete the task.

The convergence of reinforcement learning models is also an important issue. In complex environments and tasks, reinforcement learning algorithms may not converge to the optimal strategy, or the convergence speed may be very slow. This is because reinforcement learning requires searching and learning in a large number of state and action spaces, which can easily lead to getting stuck in local optima. In robot path planning tasks, if reinforcement learning algorithms get stuck in local optima, the robot may find a path that can reach the target, but this path is not globally optimal and may consume more time and energy. Moreover, when the environment changes, the converged strategies may no longer be applicable and require relearning, which also increases the uncertainty of robot decision-making.

The generalization of reinforcement learning models also faces challenges. Generalization refers to the ability of a model to apply learned knowledge in unseen environments and tasks. Due to the complexity and diversity of the actual environment, the strategies learned by reinforcement learning models in the training environment may not be effective in the new environment. When training robots to navigate indoors, the strategies learned by the model may depend on specific landmarks and layouts in the training environment. When the robot enters a new indoor environment with different layouts and landmarks from the training environment, the model may not be able to navigate accurately, resulting in problems such as getting lost or colliding. These uncertainties at the model level need to be addressed by improving the model architecture, optimizing training algorithms, and introducing more prior knowledge.

3.3. Uncertainty at the Environmental Level

In practical applications, robots inevitably face complex and ever-changing real-world environments, which contain many uncertain factors that pose a severe challenge to their intelligent control.

Environmental interference is one of the common sources of uncertainty. In different physical environments, robots are subject to various interferences that affect the normal operation of their sensors and their own motion control. In strong light environments, camera image capture may experience overexposure, resulting in loss of image information and making it difficult for robots to accurately identify surrounding objects; In noisy environments, speech recognition systems may not accurately capture human instructions, affecting robots' understanding and execution of tasks; In complex terrain conditions, such as rugged mountain roads or muddy ground, the movement of robots may be hindered, making their motion control difficult and prone to slipping, falling, and other situations.

Changes in task requirements are also an important manifestation of environmental uncertainty. With the dynamic changes in practical application scenarios, the task requirements faced by robots may change at any time. In the logistics and warehousing scenario, the robot's original task was to transport goods according to established orders, but suddenly received an urgent order that needed to be prioritized. This requires the robot to quickly adjust its strategy, re plan the path and task sequence. Moreover, the complexity of the task may also dynamically increase, for example, in the initial task, only a single type of cargo needs to be transported, and later multiple different specifications and weights of cargo may need to be transported simultaneously, which puts higher demands on the robot's grasping, transportation, and operation capabilities, increasing the difficulty of its decision-making and execution. The uncertainty at the environmental level requires robots to have stronger adaptability and robustness, to be able to perceive changes in the environment in real time and flexibly adjust their behavior strategies to ensure the smooth completion of tasks.

4. The Application Scenarios and Management Significance of Fusion Technology in Intelligent Robot Control

4.1. Industrial Production Scenarios

In industrial production, robots that integrate reinforcement learning and large language models can perform complex assembly tasks. The big language model generates assembly steps based on product assembly instructions, and reinforcement learning enables robots to learn optimal operational strategies in different assembly states through continuous experimentation. This improves assembly efficiency and accuracy, reduces scrap rates, and lowers production costs. From a management perspective, enterprises can use this technology to optimize production processes, reduce reliance on manual assembly, alleviate labor shortages, while improving production flexibility, quickly adapting to product design changes, and enhancing market competitiveness. For example, after a certain electronic product manufacturing enterprise introduced such robots, the production efficiency of the assembly line increased by 30% and the scrap rate decreased by 20%.

4.2. Logistics Distribution Scenarios

In logistics distribution, robots need to complete tasks such as cargo handling and sorting in complex warehouse environments. The big language model understands delivery order information, plans robot pickup and delivery routes, and prioritizes tasks. Reinforcement learning enables robots to dynamically adjust their action strategies based on real-time environmental changes, such as changes in shelf positions or interference from other robots. This improves logistics delivery efficiency, reduces delivery time, and lowers logistics costs. At the enterprise management level, this technology can be used to optimize logistics resource allocation, improve warehouse space utilization, enhance logistics service quality, attract more customers, and increase enterprise revenue. After a large logistics enterprise applied this technology, the turnover efficiency of warehouse goods increased by 40%, and the on-time delivery rate increased to 95%.

4.3. Medical Service Scenarios

In the field of medical services, robots can assist doctors in performing surgeries, caring for patients, and more. The big language model understands medical instructions and patient condition information, and formulates operation plans for robots, such as surgical step planning for surgical robots and patient care plans for nursing robots. Reinforcement learning enables robots to adjust their actions in real-time based on changes in the patient's physiological state and feedback from surgical instruments during actual operations, ensuring safe and accurate operations. From a management perspective, this helps medical institutions improve the quality of medical services, reduce medical accidents, enhance patient satisfaction, and allocate medical resources reasonably to improve hospital operational efficiency. For example, after a hospital adopted a nursing robot with fusion technology, the patient's nursing quality score increased by 15 points (out of 100), and the workload of nursing staff decreased by 25%.

5. Uncertainty Analysis of Robot Intelligent Control System Integrating Reinforcement Learning and Large Language Model

5.1. Uncertainty brought by reinforcement learning

The learning process of reinforcement learning has randomness, and when agents explore the environment, their action choices are influenced by policy uncertainty. In Q-Learning algorithms, agents may choose actions that are not currently optimal due to exploring new actions, resulting in unstable rewards. The uncertainty of environmental state transitions also increases the difficulty of reinforcement learning. In practical robot applications, the environment is complex and ever-changing, and state transitions are difficult to accurately model. For example, when robots navigate in unstructured environments, factors such as sensor noise and dynamic changes in the environment create uncertainty in state transitions, which may result in the robot learning strategies that are not globally optimal and affect task execution effectiveness.

5.2. Uncertainty brought by large language models

The big language model suffers from the problem of "illusion", which refers to the generation of seemingly reasonable information that does not match the facts. In the intelligent control of robots, task plans or instructions generated by large language models may contain incorrect information, misleading the robot's actions. The big language model has certain deviations in understanding input text, especially when dealing with fuzzy and ambiguous text, which may lead to misunderstandings of task objectives or environmental information, resulting in incorrect decisions and affecting the accuracy of robot task execution.

5.3. Uncertainty caused by environmental factors

The complex and ever-changing environment in which robots operate increases the uncertainty of intelligent control. In outdoor environments, factors such as weather changes and terrain undulations affect the perception and action of robots. Rainy weather can reduce the accuracy of visual sensors, and complex terrain may increase the difficulty of robot motion control. In indoor environments, changes in personnel movement and object placement can also interfere with the operation of robots. These environmental uncertainties may make it difficult for reinforcement learning models to accurately predict environmental state transitions, and large language models may have biases in understanding environmental information, ultimately affecting the stability and reliability of robot intelligent control.

6. Management Strategies for Dealing with Uncertainty

6.1. Optimization Model Training and Parameter Adjustment

Enterprise managers should organize a professional technical team to optimize and train reinforcement learning and big language models. In reinforcement learning training, it is important to adjust the balance parameters between exploration and utilization, such as reducing the exploration rate in Q-Learning, minimizing unnecessary exploration, and improving strategy stability. For large language models, using more high-quality data for pre training and fine-tuning can reduce the probability of "illusion" problems and improve the accuracy of the model's text understanding. By regularly evaluating model performance and adjusting training data and parameters in a timely manner, we ensure the adaptability and reliability of the model in different environments.

6.2. Establish multiple verification and feedback mechanisms

Establish a multi validation mechanism to validate the task planning generated by the large language model and the action strategies generated by reinforcement learning before the robot performs tasks. Simulated environment testing can be used to run plans and strategies in a simulated environment, checking for any obvious errors or inconsistencies. At the same time, a real-time feedback mechanism is established during the execution of tasks by robots to collect operational data, environmental information, and task execution results. Problems are promptly identified and fed back to the model for adjustment. If the robot encounters unreasonable path planning in logistics distribution, the feedback mechanism will transmit the problem information to the big language model and reinforcement learning model, and the model will optimize subsequent decisions based on the feedback.

6.3. Improving Environmental Adaptability and Robust Design

During the robot design phase, emphasis is placed on improving its environmental adaptability and robustness. Adopting multi-sensor fusion technology, such as vision, LiDAR, ultrasonic sensors, etc., to improve the accuracy and reliability of robot perception of the environment, and reduce the impact of environmental interference on a single sensor. Optimize the hardware of the robot to enhance its motion stability and reliability in complex environments. At the software level, develop environment adaptive algorithms to enable robots to automatically adjust strategies based on environmental changes, improving their ability to cope with environmental uncertainty. For example, robots can automatically adjust sensor parameters and motion control strategies under different outdoor weather conditions to ensure the normal execution of tasks.

7. Conclusion

The integration of reinforcement learning and big language models brings broad prospects for the intelligent control of robots, demonstrating enormous application potential in various fields such as industrial production, logistics and distribution, and medical services. It has important management significance for enterprises to optimize production processes, improve operational efficiency, and enhance service quality. However, the uncertainties associated with this fusion technology, such as the randomness of reinforcement learning and difficulties in environmental modeling, the "illusion" of large language models and text comprehension biases, and interference from complex environmental factors, may affect the stability and reliability of robot intelligent control. By adopting management strategies such as optimizing model training and parameter adjustment, establishing multiple validation and feedback mechanisms, and improving environmental adaptability and robustness design, the impact of uncertainty can be effectively reduced, promoting the widespread application and sustained development of fusion technology in the field of robot intelligent control. In the future, with the continuous advancement of technology, the integration of reinforcement learning and big language models will become more mature, injecting new impetus into the intelligent development of robots and bringing more innovative opportunities and changes to various industries.

References

[1] Dixon,Warren.Optimal Adaptive Control and Differential Games by Reinforcement Learning Principles[J].IEEE Control Systems, 2014, 34(3):80-82.

[2] [2] Xu M, Wang J .Deep Reinforcement Learning for Parameter Tuning of Robot Visual Servoing[J].ACM transactions on intelligent systems and technology, 2023, 14(2):33.1-33.27.

[3] Bakker B, Zhumatiy V , Gruener G .A Robot that Reinforcement-Learns to Identify and Memorize [C] // Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453).

[4] Kamalapurkar R , Walters P , Dixon W E .Model-based reinforcement learning for approximate optimal regulation [J].Pergamon Press, Inc. 2016.

[5] Ma R, Luijkx J , Ajanovic Z ,et al.ExploRLLM: Guiding Exploration in Reinforcement Learning with Large Language Models[J]. 2024.

[6] Li Y, Zhou W , Wang H ,et al.Improving Fast Adaptation for Newcomers in Multi-Robot Reinforcement Learning System [J].2019 IEEE SmartWorld, 2019:753-760.

[7] Zhang R , Zhao C , Du H ,et al.Embodied AI-Enhanced Vehicular Networks: An Integrated Large Language Models and Reinforcement Learning Method [J]. 2025.

[8] Liu T, Yang Y , Xiao W ,et al.A Comparative Analysis of Deep Reinforcement Learning-Enabled Freeway Decision-Making for Automated Vehicles[J].IEEE Access, 2024:12.