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ADAPTIVE CONTROL STRATEGIES FOR ROBOTIC MANIPULATORS USING DEEP REINFORCEMENT LEARNING

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Abstract

This research examines adaptive control strategies for robotic manipulators using Deep Reinforcement Learning (DRL) through a systematic literature review approach. The main focus of the study is the identification of commonly used DRL algorithms, implementation challenges, and the direction of developing DRL-based adaptive control systems. The study results show that algorithms such as DDPG, SAC, and PPO are effective in addressing the non-linear dynamics and uncertainties of robotic manipulators, both in simulation and real-world environments. However, there are significant challenges such as the

need for large training data, the simulation-to-real gap, and the limitations in the interpretability of control policies. The integration of hybrid control strategies, the development of more sample-efficient algorithms, and the application of hierarchical and meta-reinforcement learning have been identified as promising future research directions. This study provides a foundation for the development of more flexible, efficient, and safe robotic control systems to support various industrial applications.
Keywords: Adaptive Control, Robotic Manipulator, Deep Reinforcement Learning

INTRODUCTION

The development of robotic technology in the last decade has seen significant improvements, particularly in the field of robotic manipulators. Robotic manipulators are widely used in the manufacturing, medical, and even space exploration industries. This system requires a high level of precision, speed, and flexibility in its control. In facing a dynamic work environment, robots must be able to adapt to changing conditions in real-time (Yanover & Choukroun, 2024). Therefore, the need for adaptive control systems is becoming increasingly important to enhance the performance of manipulators. Adaptive control technology has become one of the promising approaches to address this challenge.

Adaptive control in robotic manipulators focuses on the system's ability to automatically adjust control parameters according to changes in system or environmental characteristics. Robotic manipulators often face variations in load, friction, and uncertainties in dynamic models that cannot be fully predicted in advance. This condition causes control using conventional methods such as PID (Proportional-Integral-Derivative) to become less effective. Adaptive control systems are expected to provide solutions by continuously adjusting parameters without human intervention (Pei & Lan, 2023). This allows robotic manipulators to operate more efficiently and stably. However, designing an effective adaptive control strategy is not a simple task.

One of the main challenges in controlling robotic manipulators is the high complexity of the dynamic model. Manipulators have many degrees of freedom (Degrees of Freedom/DOF) which cause the non-linear interactions between their components to become very complex. Additionally, factors such as parameter uncertainty, external disturbances, and environmental changes increase the level of difficulty in designing reliable control systems. Accurate mathematical models are often difficult to obtain in practice, so control methods that do not heavily rely on models are needed. Adaptive control offers the ability to overcome these limitations through feedback-based adjustments (Kashkash et al., 2024). However, the implementation of conventional adaptive control still has limitations, particularly in terms of efficiency and stability.

With the advancement of artificial intelligence, approaches based on Deep Reinforcement Learning (DRL) have begun to be introduced in robotic control. DRL is a combination of Reinforcement Learning (RL) and Deep Learning that allows agents to learn control strategies directly from sensor data or simulations. This method is capable of handling high-dimensional systems and complex environments without requiring an explicit dynamic model. By leveraging the structure of neural networks, DRL is capable of approximating complex control policy functions and adapting flexibly to environmental changes (Ge, 2024). This provides a great opportunity for the development of adaptive control systems for robotic manipulators. DRL has shown promising results in various experimental studies, both in simulations and on real robots.

Nevertheless, the application of DRL in adaptive control of robotic manipulators is not without its own challenges. One of the main issues is the need for a very large amount of training data for the DRL agent to learn optimal strategies. The exploration process carried out by DRL agents often requires a long time and significant computational resources. Additionally, there is a risk of instability during the training process that can cause physical damage to the robot if applied directly (Zhang & Mo, 2023). Therefore, special strategies such as simulation beforehand are necessary before applying it in the real world (sim-to-real transfer). These issues have become a primary concern in the further development of DRL technology for adaptive robotic control.

Current research trends show efforts to address the limitations of DRL through various hybrid approaches. One of them is by combining conventional adaptive control with DRL, resulting in a control system that is both more stable and flexible. This approach allows for the utilization of the advantages of both methods, namely the stability of conventional control and the adaptability of DRL. Additionally, the development of more sample-efficient DRL algorithms such as Soft Actor-Critic (SAC) and Twin Delayed DDPG (TD3) is also becoming increasingly popular. These algorithms are capable of reducing the need for training data without sacrificing control performance

(Yang et al., 2024). Thus, the integration of DRL into adaptive control of robotic manipulators is becoming increasingly feasible for implementation.

In various literature studies, the application of DRL has been found in various types of manipulators, ranging from simple robotic arms to complex humanoid robots. These studies show that DRL can improve the accuracy and robustness of robot control systems against disturbances and parameter changes. Several studies also report that DRL can overcome the limitations of traditional adaptive control methods, particularly in highly dynamic and unstructured environments (Pan et al., 2023). However, it should be acknowledged that most experiments are still conducted in simulated environments. Therefore, it is important to conduct further research to ensure that the control strategies developed through DRL can be effectively implemented in the real world. Validation in a physical environment becomes a crucial step in this process.

Based on the aforementioned description, it is important to conduct a comprehensive literature review on adaptive control strategies for robotic manipulators using Deep Reinforcement Learning. This study aims to summarize various approaches, algorithms, and challenges that have been identified in previous research. Thus, a clearer picture can be obtained regarding the advantages and disadvantages of each existing control strategy. This study is also expected to provide direction for the development of further research in the field of DRL-based robotic control. Such research has great potential in enhancing the efficiency and flexibility of robotic systems across various industrial sectors. In addition, the results of this study can serve as a reference for practitioners and researchers interested in developing adaptive control systems based on artificial intelligence.

RESEARCH METHOD

This literature review uses a systematic literature review (SLR) approach to obtain a comprehensive understanding of adaptive control strategies for robotic manipulators using Deep Reinforcement Learning (DRL). The review process begins by establishing the inclusion and exclusion criteria for the articles to be reviewed (Snyder, 2019; Tranfield et al., 2003). The articles included in this study are English-language scientific publications, published between 2015 and 2025, specifically discussing the application of DRL in the control of robotic manipulators or similar robotic systems. Articles that only discuss DRL theory without implementation in robotic systems, as well as articles that have not undergone the peer-review process, are excluded from the study. In addition, only articles from reputable journals and proceedings were selected to maintain the validity of the study's results.

The main data sources in this study include leading scientific databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar as additional support. The identification process begins with a search using keywords such as "adaptive control," "robot manipulator," "deep reinforcement learning," and "robotic control strategy." After the identification stage, a selection process is carried out by reading abstracts and topic relevance based on the established criteria. Relevant articles are then further analyzed through data extraction related to control methods, the DRL algorithms used, types of manipulators, as well as reported results and challenges. This process ensures that the literature review conducted is systematic, transparent, and can be replicated by other researchers.

RESULT AND DISCUSSION

Application of Deep Reinforcement Learning (DRL) Algorithm in Robotic Manipulator Control

In recent years, Deep Reinforcement Learning (DRL) algorithms have become a major focus in the development of adaptive control for robotic manipulators. DRL leverages the ability to learn from interactions with the environment to optimize control strategies. The main advantage of DRL is its ability to handle the dynamics of non-linear and complex systems without requiring precise mathematical models (Calderon-Cordova & Sarango, 2023). This makes DRL highly relevant for robotic manipulators with many degrees of freedom. With various algorithms developed, DRL has proven effective in controlling the position, speed, and force of manipulators. This condition encourages more and more research and experiments to be conducted in this field.

Some of the most widely applied DRL algorithms include Deep Deterministic Policy Gradient (DDPG), Soft Actor-Critic (SAC), and Proximal Policy Optimization (PPO). These three algorithms have specific characteristics that enable them to tackle specific challenges in robotic manipulator control. DDPG is known to be effective for continuous control problems, where manipulators require smooth and precise motion adjustments (Heaton & Givigi, 2023). SAC offers better stability in the learning process by utilizing the concept of entropy regularization, making the control policy more exploratory yet still safe. PPO is widely used because of its ability to combine stability and training efficiency in various environmental conditions. The choice of algorithm is often tailored to the specific needs of the developed robotic application.

The application of DRL in adaptive control provides high flexibility for robotic manipulators. Unlike traditional control methods that require strict parameter design, DRL allows robots to automatically adapt to changes in the environment or load. The system can learn new strategies solely through trial-and-error, without direct human intervention (Malik et al., 2022). This is very useful in situations where dynamic models are difficult to formulate mathematically. For example, in a volatile industrial environment, DRL allows manipulators to adjust their controls to remain optimal. This flexibility becomes the main advantage of DRL compared to conventional methods.

Based on the literature review, DRL has proven to be effective not only in simulation environments but is also beginning to be applied to real robotic manipulators. Several experiments have shown that DRL is capable of controlling robots stably even in the presence of disturbances or uncertainties in system parameters. However, direct application on physical robots requires special attention to safety and system stability factors. The exploration process conducted by the DRL algorithm can lead to undesirable movements, so mitigation strategies such as pre-training in simulation are highly recommended (Abiola et al., 2023). Additionally, additional oversight mechanisms are needed to avoid damage to the robot's hardware during the training process. This shows that although DRL is promising, its application in the real world requires a more cautious approach.

The end-to-end approach in DRL is increasingly being developed in robotic manipulator control. In this approach, input from sensors such as cameras, lidar, or force sensors is processed directly by the neural network in DRL to generate control actions. This is different from the traditional approach that requires manual processing or feature extraction before decision-making. The advantage of this approach is the simplicity of the system architecture and higher adaptability. However, the main challenge of the end-to-end approach is the need for a very large amount of training data and high computational complexity (Majumder & Sahoo, 2024). Therefore, research is still ongoing to optimize the efficiency and reliability of this approach.

In addition, the integration of DRL with conventional control systems is also becoming a strategy that is increasingly applied in robotic manipulator control. This combination aims to leverage the advantages of each approach, namely the stability of conventional control and the adaptability of DRL. For example, the use of a PID controller as baseline control, while DRL is tasked with adapting parameters or adjusting certain aspects of the control. This approach is also useful for accelerating the DRL training process because the robot has a stable behavioral foundation from the beginning (Zhang & Mo, 2023). This integration allows for a reduction in risk during experiments in real-world environments. Several studies report positive results with this hybrid approach, although further testing is still needed.

Another important aspect in the application of DRL for manipulator control is the adjustment to the type and configuration of the manipulator itself. Manipulators with two to six degrees of freedom require different strategies in terms of policy design and DRL parameter settings. The more complex the manipulator, the larger the action space dimension that must be managed by the DRL algorithm. This directly affects the computational load and the time required to achieve the optimal policy. Therefore, the design of the neural network architecture in DRL must be carefully adjusted to the configuration of the manipulator being used (Liu & Li, 2023). Recent research has extensively discussed network design optimization to reduce this complexity without compromising system performance.

Overall, the application of DRL in robotic manipulator control has opened new opportunities in the development of smarter and more adaptive robotic systems. Although there are various challenges, the results from various studies indicate that DRL has great potential for widespread application, especially in the fields of industry and services. This application is not limited to position and speed control, but is also beginning to extend to force control, object manipulation, and human-robot interaction. With the continuous advancement of computing technology and more efficient DRL algorithms, it is hoped that the implementation of DRL-based adaptive control systems can become the new standard in robotics technology. Further research is still needed to address practical constraints and improve the overall system efficiency. However, the direction of the development of this technology shows a very positive and promising trend.

Challenges and Issues in Implementing DRL in Adaptive Manipulator Control

The implementation of Deep Reinforcement Learning (DRL) in adaptive control of robotic manipulators faces significant challenges related to the need for very large training data. The learning process in DRL requires thousands to millions of interaction episodes for the agent to form an optimal control strategy. This certainly requires substantial computational resources, both in terms of time and hardware. This challenge becomes even more difficult when training is conducted directly on physical robots because it incurs operational costs and poses a risk of damage (Yan et al., 2022). Therefore, most research still relies on simulations as an initial stage before real-world implementation. However, the use of simulations is not without limitations, especially in terms of alignment with actual physical conditions.

In addition to the need for data, the stability of the exploration process in DRL also poses a crucial challenge. DRL algorithms require exploration mechanisms to find the best policies, but in practice, this exploration often results in unexpected actions. In robotic manipulators, unstable or extreme actions can result in damage to mechanical components or even endanger the safety of the operator. This problem is exacerbated when control is performed in real-time without adequate safety constraints (Atti & Yogi, 2024). Therefore, many studies propose additional safety strategies, such as using action clipping or integrating a safety supervisor system. These challenges make the development of DRL-based adaptive control require a more careful and systematic approach.

The gap between training results in simulation and performance in the real world, known as the sim-to-real gap, becomes another major issue in the application of DRL for robotic manipulators. The simulations used to train DRL agents often do not fully represent the complexity and uncertainty of the physical environment (Campos et al., 2022). This causes strategies that are already optimal in simulation not to always work effectively when applied directly to physical robots. Factors such as model inaccuracies, sensor differences, and variations in the real environment are the main causes of this sim-to-real gap. Several techniques such as domain randomization and transfer learning have been developed to reduce this gap, but their effectiveness still needs to be improved. Therefore, direct testing in real environments remains a crucial stage before DRL is widely implemented in the industry.

The next challenge is the trade-off that occurs between exploration and exploitation in DRL algorithms, which directly impacts the stability of the control policy. If the agent explores too much, the training process becomes slower and the resulting policy is difficult to stabilize. On the other hand, if exploitation is more dominant, the agent may not find a truly optimal policy because it stops learning too quickly. This trade-off is very important to consider in the context of robotic manipulator control, as motion stability significantly affects system safety and performance (Bashendy et al., 2024). Parameter settings such as learning rate, entropy coefficient, and exploration noise are key to maintaining the balance between exploration and exploitation. However, the tuning process itself requires specialized expertise and often takes a considerable amount of time.

The complexity of the structure and dynamics of robotic manipulators also adds challenges in the application of DRL. The more degrees of freedom the manipulator has, the larger the dimensions of the action space and state space that the DRL agent must learn (Arshad & Bazzocchi, 2024). This leads to an increase in computational load and difficulty in achieving stable policy convergence. Additionally, changes in load or external disturbances can worsen the stability of the system if the trained control policy is not robust enough. Therefore, special strategies are needed, such as the use of hierarchical reinforcement learning or modular control, which divide control tasks into simpler sub-tasks. This approach aims to reduce complexity and improve the efficiency of the training process.

On the other hand, the limited interpretability of policies generated by DRL has become one of the important issues that are often overlooked. Unlike traditional control methods that have a clear mathematical basis, DRL policies often take the form of non-linear functions that are difficult to analyze or intuitively understand. This complicates the processes of debugging, error analysis, as well as verification and validation of control systems, especially in industrial contexts that require high safety standards. Some approaches, such as explainable reinforcement learning, have begun to be introduced to address this issue, but they still require further development. Without adequate interpretability, user trust in DRL-based adaptive control systems becomes limited (Zeng et al., 2023). Therefore, this aspect needs to receive special attention in further research.

Besides technical factors, the challenges in implementing DRL are also related to the cost and infrastructure aspects required. The development and implementation of DRL for robotic manipulators require supporting hardware, such as high-capacity GPUs, precise sensors, and realistic simulation devices. This investment is not always affordable, especially for medium and small-scale industries that want to implement adaptive robotic technology. This has become one of the factors limiting the adoption of DRL in the broader industrial sector (Yang et al., 2024). Therefore, efforts are needed to develop lighter and more efficient algorithms so that they can be implemented with more limited resources. Innovations in the field of hardware can also help reduce these barriers in the future.

Overall, the challenges discussed indicate that the application of DRL in adaptive control of robotic manipulators still requires significant improvements, both in terms of algorithms, system architecture, and practical implementation. Nevertheless, the continuous development of technology and research opens up opportunities to gradually overcome these challenges. The main focus moving forward is to develop DRL algorithms that are more sample-efficient, safe, and easy to implement across various types of manipulators with different levels of complexity. Additionally, collaboration between algorithm developers, robotic engineers, and industry practitioners is key to accelerating the real-world adoption of this technology. With a systematic and collaborative approach, DRL-based adaptive control has great potential to become one of the standards in the control of future robotic manipulators.

Integration of Hybrid Control Strategies and Future Research Directions

The integration between Deep Reinforcement Learning (DRL) and conventional control methods is increasingly being applied as a solution to the limitations of each approach. Conventional control methods such as PID (Proportional-Integral-Derivative) are known for their high stability and reliability, but they are less flexible in adapting to environmental changes. Meanwhile, DRL offers high adaptability, but still faces challenges related to stability and the need for large amounts of data. By combining both, the control system can leverage the advantages of both methods simultaneously (Feng et al., 2023). In practice, conventional control usually serves as baseline control, while DRL adjusts parameters or optimizes specific parts of the system. This approach not only improves performance but also accelerates the learning process because the robot does not need to learn from scratch.

One of the most researched forms of integration is the combination of Model Predictive Control (MPC) with DRL. MPC is known for its ability to predict system behavior several steps ahead and optimize actions based on those predictions. When combined with DRL, MPC plays a role in maintaining the stability and safety boundaries of the system, while DRL manages more flexible long-term policies. This approach has proven effective in reducing risk during the exploration phase, especially when applied directly to physical robotic manipulators (Xiao, 2023). Several studies show that the integration of MPC-DRL can enhance energy efficiency while maintaining the accuracy of position and force control. Nevertheless, this integration requires more complex calculations and more careful system design.

Hierarchical Reinforcement Learning (HRL) and Meta-Reinforcement Learning (Meta-RL) are other approaches that are beginning to be applied to enhance the efficiency and flexibility of adaptive control. HRL divides control tasks into several hierarchical levels, where the upper level determines long-term goals and the lower level manages specific actions. In this way, the complexity of the action space can be reduced, thereby accelerating the learning process and enhancing policy stability (Shen et al., 2022). Meanwhile, Meta-RL allows the learning system to learn, that is, to adapt more quickly to new environments with previous experiences. This approach is highly relevant in the context of robotic manipulators that must operate in various situations with different characteristics. The development of HRL and Meta-RL is still in its early stages, but its potential is quite promising for widespread application.

In addition to the development of algorithmic structures, much research also focuses on improving sample efficiency and the convergence speed of DRL. Algorithms such as Twin Delayed Deep Deterministic Policy Gradient (TD3) and Soft Actor-Critic (SAC) have been developed to address the issue of overestimation bias and enhance learning stability. Modifications such as adjusting the learning rate parameters, entropy regularization, and the use of more sophisticated replay buffers continue to be explored. The main goal is to reduce the amount of data required so that the system can learn effective control policies (Majumder & Sahoo, 2024). This is very important in the context of robotic manipulators because the process of collecting data from the real world requires significant time and cost. With more efficient algorithms, it is hoped that the application of DRL in the industry can become more practical and affordable.

Future research trends are also directed towards reducing the sim-to-real gap, which has been the main obstacle to implementing DRL in real-world environments. Techniques such as domain randomization, where various environmental parameters are randomized during simulation, aim to make DRL agents more robust when transferred to the physical world. Additionally, transfer learning methods and direct policy fine-tuning on physical robots are also beginning to be implemented to accelerate the adaptation process. Other research focuses on the development of more realistic and accurate simulators to approximate actual physical conditions. Although progress has been made, the challenge of ensuring that policies trained in simulation remain effective and safe in the real world continues to be a major concern

(Sehgal et al., 2022). Therefore, sim-to-real transfer will remain one of the priorities in the development of DRL-based adaptive control systems. The issue of interpretability of control policies is also an important concern in the development of DRL for robotic manipulators. The policies generated by DRL often take the form of complex non-linear functions that are difficult for humans to analyze. In the industrial context, where safety and reliability are crucial, the inability to understand how policies work becomes a serious obstacle. Therefore, research is beginning to focus on the development of explainable reinforcement learning (XRL), which aims to make DRL policies more transparent and logically explainable. Techniques such as neural network visualization, dimensionality reduction, and the use of interpretable models as proxies have begun to be introduced (Wang et al., 2024). With the increasing need for auditable and accountable control systems, the development of XRL will become an important part of future research directions.

In addition to technical aspects, attention is also being given to the development of safer and industry-compliant adaptive control systems based on DRL. Several international robotic safety standards require strict validation and verification of control systems before they are commercially implemented. Therefore, the integration of hybrid DRL control with monitoring mechanisms or fail-safe systems is becoming an increasingly relevant topic. Research has begun to combine DRL with formal methods and logic-based control to ensure that the system remains within the established safety boundaries (Zhong et al., 2024). This is important for building trust from the industrial sector towards new technologies such as DRL. Thus, the development of safe and standardized systems becomes part of the long-term research strategy.

Overall, the integration of hybrid control strategies between DRL and conventional methods opens up significant opportunities to enhance the performance of robotic manipulators in various industrial sectors. The direction of future research not only focuses on improving the efficiency and stability of algorithms but also on developing systems that can be practically applied and meet existing safety standards. With the continuous advancement of technology and collaboration between academics, industry practitioners, and technology developers, it is hoped that DRL-based adaptive control can become an integral part of future robotic systems. Innovation in the fields of hardware, algorithms, and simulation methodologies will also play a crucial role in accelerating the adoption of this technology. Therefore, the development of hybrid control strategies with DRL remains one of the most dynamic and relevant research fields to this day.

CONCLUSION

Based on the literature review conducted, it can be concluded that adaptive control strategies for robotic manipulators using Deep Reinforcement Learning (DRL) show great potential in enhancing the flexibility and efficiency of control systems. Algorithms such as DDPG, SAC, and PPO have proven capable of handling non-linear dynamics and environmental uncertainties without requiring an explicit dynamic model. However, there are several main challenges such as the need for large training data, the stability of the exploration process, and the gap between simulation results and real-world applications (sim-to-real gap). The integration of hybrid control, the development of more sample-efficient algorithms, and approaches such as hierarchical reinforcement learning have become widely researched trends to address these issues. These findings have important implications for the future development of robotic control systems, particularly in realizing manipulators that are more adaptive, safe, and easy to implement across various industrial sectors.

As a recommendation for further research, it is necessary to focus on the development of DRL algorithms with higher data efficiency to reduce computational load and risk in the training process. Techniques such as transfer learning, meta-reinforcement learning, and the use of more efficient replay buffers can be the focus of the next development. Additionally, it is important to conduct direct validation in real environments to ensure that the control policies trained in simulations can function well and safely when applied. Research is also advised to pay more attention to the aspects of interpretability and system security, particularly in the context of industrial applications. With this development direction, it is hoped that DRL-based adaptive control can become increasingly effective, efficient, and reliable to support the needs of modern robotic systems.

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