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AUTONOMOUS GRASPING CONTROL VIA DEEP LLM IN AEROSPACE ROBOTICS

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1. Introduction

As the paradigms of aerospace robotics continue to evolve, the integration of advanced computational frameworks has heralded a transformative shift in the domain [1-4]. This shift, often aligned with the concept of the "Fourth Industrial Revolution," extends beyond terrestrial manufacturing to encapsulate the unique challenges and opportunities presented by extraterrestrial environments. The infusion of intelligent robotics into space exploration and operations seeks to optimize autonomous performance, enhance operational efficiency, and ensure reliability under the constraints of microgravity and environmental uncertainty.

While the advancements in aerospace automation represent a significant leap, they are merely the prelude to the full potential of this domain [5]. For decades, autonomous systems have been employed to mitigate the human workload and augment efficiency, particularly in mission-critical tasks such as satellite servicing [6], debris removal [7], and extraterrestrial construction [8]. However, traditional paradigms often rely on fixed operational frameworks, which limit adaptability and scalability in dynamic and unpredictable space environments.

This research pivots toward a more adaptive and context-aware framework, leveraging the capabilities of large language models (LLMs) integrated with advanced robotic control algorithms. By embedding these linguistic and cognitive models within the operational architecture of aerospace robotics, systems can achieve an unprecedented level of autonomy and contextual reasoning. Such integration not only facilitates precise navigation and manipulation tasks but also allows the robotic agents to infer, adapt, and respond to unforeseen contingencies effectively.

The rapid advancements in collaborative robotic systems, particularly those designed to operate in conjunction with other robots and human operators, further underscore the relevance of this approach. In [9], the author represents a milestone in adaptive robotics, introducing robust decentralized control mechanisms that redefine the standards of satellite servicing, which bridges military objectives of resilience with commercial aspirations for sustainability and paving the way for innovative solutions in defense and aerospace industries, including pioneers like SpaceX. This next generation of aerospace robots, equipped with LLM-powered decision-making and control frameworks, embodies the confluence of advanced robotics, artificial intelligence, and space engineering, paving the way for more resilient and adaptive solutions in the ever-expanding frontier of space exploration [10].

The advent of autonomous systems, intelligent robotics, and machine learning has initiated a paradigm shift in the operational capabilities of aerospace robotics. For example, [11] introduces a paradigm shift in robotic control, integrating deep learning with robust MPC for high-DoF manipulators. It offers transformative solutions for science and technology, bridging gaps between adaptability, precision, and real-time learning, thereby setting a benchmark for innovation in aerospace, defense, and commercial robotics. Within the context of space exploration, robotics serves as a cornerstone for advancing mission-critical tasks such as object manipulation, satellite maintenance, and payload management under highly constrained and dynamic conditions. The inherent complexities of microgravity and the unpredictable nature of space necessitate novel methodologies that synergize advanced computational frameworks with adaptive robotic architectures [12-15].

Figure 1. A spacecraft module grappled by a Space Station's robotic arm[1].

2. Related Work

One of the foremost challenges in aerospace robotics lies in accurately manipulating objects within unstructured environments where gravitational forces are absent, and sensory data is often sparse or inconsistent [16]. In contrast to terrestrial robots, which rely heavily on predefined kinematic models and controlled environments, space robots must dynamically interpret their surroundings to identify, approach, and manipulate targets with precision. While traditional approaches such as stereoscopic vision, LiDAR, and motion planning algorithms provide a foundational framework, they often lack the adaptability required to operate seamlessly in the vast and volatile domain of space.

Addressing these challenges, [17] introduces an innovative methodology that using Monte Carlo Tree Search (MCTS) framework tailored for strategic decision-making under computational constraints, providing pivotal insights into efficient algorithm design for aerospace robotics. The novel CPU and GPU-based implementations reveal groundbreaking improvements in simulation scalability and resource optimization, directly influencing applications like autonomous navigation,

[1] The picture from Spaceflight Now, credit by Lockheed Martin

spacecraft servicing, and robotic decision-making in uncertain and dynamic environments. Its contribution establishes a benchmark for computational algorithms in aerospace, bridging innovative robotics solutions with real-time operational challenges. LLMs enable a deeper contextual understanding of the environment, facilitating dynamic decision-making and task prioritization in real-time [18]. By employing a six-degrees-of-freedom robotic manipulator augmented with YOLOv5 for precise object detection and backward projection for 3D spatial localization, the proposed framework ensures robust and efficient grasping in low-gravity scenarios [19-22].

This approach tackles the inverse dynamics problem by combining the analytical precision of deterministic models with the adaptive flexibility of data-driven reinforcement learning techniques [23]. Specifically, the trust region policy optimization (TRPO) algorithm is utilized to train the robotic system, enabling autonomous computation of joint angles for efficient object manipulation. The proposed framework extends its applicability to multi-degree-of-freedom robotic systems [24], thereby providing a versatile solution tailored to the exigencies of aerospace environments.

In summary, the core contributions of this research are as follows:

- The integration of deep learning method based LLMs for enhanced contextual reasoning and decision-making in dynamic environments.
- The application of YOLO-v8 for real-time object detection and precise spatial localization.
- A robust inverse kinematics solution incorporating TRPO for autonomous manipulation of spaceborne objects.
- Validation of the methodology through simulations that demonstrate its superiority over state-of-the-art techniques, achieving high accuracy and reliability in task execution.

This study represents a significant advancement in the domain of aerospace robotics, paving the way for autonomous systems that operate with unprecedented precision and adaptability in the most challenging environments known to humankind.

3. Methodology

In the realm of autonomous systems, the optimization of decision-making processes in dynamic and uncertain environments remains a paramount challenge, particularly in the context of aerospace robotics [25]. These systems must operate within the constraints of microgravity and the vast unpredictability of space, necessitating the integration of decentralized adaptive control method from [26] to deal with the uncertainty of the target payload in space environment. Reinforcement learning (RL), with its capacity to adapt and learn optimal policies through trial-and-error interactions, has emerged as a pivotal framework in addressing these complexities.

Policy-driven architectures, as central tenets of RL, aim to maximize cumulative rewards by iteratively refining value functions [27]. This approach facilitates the derivation of optimal actions from specific states, represented mathematically as $\pi^*(s) \rightarrow a$. RL paradigms are broadly categorized into value-based and policy-based methods. While value-based techniques, such as Q-learning, focus on approximating the optimal action-value function $Q^*(s, a)$ policy-based strategies directly converge on the optimal policy $\pi^*(s)$ through gradient-based optimization.

In aerospace robotics, the ability to compute precise action-value functions is instrumental in overcoming challenges such as trajectory planning, object manipulation, and adaptive control under environmental uncertainties [26]. The integration of large language models (LLMs) into RL frameworks introduces a paradigm shift, enabling advanced contextual reasoning and enhanced generalization capabilities. This hybridized approach empowers robotic systems to synthesize high-level reasoning with low-level control, thereby enhancing their operational efficacy in space environments.

Central to this methodology is the Bellman equation, which provides the theoretical underpinning for value updates in RL. The iterative process, formalized as:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

allows for continuous refinement of action-value estimates, ensuring convergence to the optimal policy. Here, α denotes the learning rate, while γ represents the discount factor, emphasizing the importance of future rewards. The error term, $\Delta(s,a,r,s')$ encapsulates the discrepancy between current and target estimates, facilitating adaptive corrections.

By embedding LLMs within this RL-driven framework, aerospace robots can dynamically infer contextual nuances, predict task-specific requirements, and autonomously execute precision maneuvers[28]. This novel approach not only addresses the operational demands of space robotics but also establishes a foundation for next-generation intelligent systems capable of navigating the uncharted frontiers of space exploration[29-33].

To accelerate the learning process and enhance convergence efficiency, particularly in the domain of aerospace robotics, we leverage the Actor-Critic (AC) framework with a robust architectural enhancement. This involves the incorporation of target networks into both the actor and critic components, ensuring stability in the learning trajectory [34]. By drawing conceptual inspiration from the Deep Q-Network (DQN) methodology, this approach is adapted to continuous action spaces, a critical requirement for high-precision tasks in the microgravity conditions of outer space[35-39].

In aerospace robotics, decision-making often involves navigating continuous state and action spaces, necessitating algorithms capable of adaptive and resilient learning. The Deep Deterministic Policy Gradient (DDPG) algorithm emerges as a quintessential off-policy strategy, designed to address these challenges effectively. This algorithm, underpinned by reinforcement learning principles, is synergized with large language models (LLMs) to augment contextual understanding and enable dynamic decision-making. By utilizing LLMs, the framework not only facilitates intuitive grasping of complex environmental nuances but also enhances policy optimization through semantic reasoning.

In this enhanced framework, target networks denoted as $Q'(s',a,w')$ an $\mu'(s',\theta')$ are systematically employed alongside the primary critic $Q(s,a,w)$ and actor networks. The critic network minimizes the temporal difference error to stabilize value function estimation [40], while the actor network optimizes the policy by leveraging gradient ascent. The corresponding loss functions for the critic and actor networks are formulated as follows:

$$U_1 = [R + \gamma Q'(s', \mu'(s', \theta'), w') - Q(s,a,w)]^2$$
$$U_2 = \nabla_a Q(s,a,w) \nabla_\theta \mu(s,\theta)$$

Here, γ represents the discount factor for future rewards, R denotes the immediate reward signal, and ∇ signifies the gradient operator used to optimize network parameters.

The integration of LLMs within the DDPG framework redefines the operational paradigms for aerospace robotic systems, enabling precise and adaptive control in uncertain space environments. This approach not only addresses the inherent complexities of inverse kinematics in multi-degree-of-freedom manipulators but also demonstrates significant improvements in convergence rates and decision-making efficacy [41]. Through this confluence of RL and LLM technologies, the research sets a new benchmark for intelligent robotic systems designed for extraterrestrial exploration and operations.

Numerous methodologies have been developed to enhance object manipulation tasks in robotic systems, yet the dynamic and unpredictable nature of the space environment poses unique challenges that transcend conventional techniques. Traditional frameworks primarily focus on robotic grasping and manipulation in terrestrial contexts, where the availability of structured environments simplifies the learning and execution processes. However, in aerospace robotics, the absence of gravitational forces, limited sensory feedback, and the high cost of computational errors necessitate an entirely novel approach to autonomous manipulation [42-47].

Recent advancements in reinforcement learning (RL) and large language models (LLMs) have opened new avenues for intelligent control in aerospace robots. LLMs, with their ability to interpret complex contextual data, enable space-based robotic systems to understand nuanced environmental dynamics and execute highly adaptive policies [48-51]. This integration of semantic reasoning with RL frameworks allows robots to make informed decisions in real-time, enhancing their ability to identify, localize, and interact with objects in microgravity.

While traditional deep reinforcement learning (DRL) strategies have demonstrated success in terrestrial applications, such as robotic grasping and stacking, their scalability to aerospace tasks remains constrained. Techniques such as self-supervised learning have been employed to teach robots object manipulation skills, leveraging mechanisms like laser-based sensors and stereoscopic vision. However, these approaches are inherently limited by their reliance on pre-defined training samples and static operational frameworks. By embedding LLMs into the learning architecture, robots can dynamically infer missing data points, predict the impact of external forces, and develop efficient manipulation strategies in unstructured space environments.

Critically, it is essential to acknowledge that the deterministic conditional mapping of outputs, as referenced in prior frameworks, constitutes an integral aspect of the hypothesized model within the Bayesian inference paradigm. Within this context, the hypothesis $\mathcal{H}$ asserts that, conditioned on the specified model parameters θ, the outputs are unequivocally determined by the governing function $f(x;\theta)$. This deterministic perspective aligns with traditional methodologies in computational modeling but often fails to accommodate the inherent uncertainties prevalent in dynamic aerospace environments [52].

By embedding LLMs within the Bayesian framework, the deterministic output function is augmented to account for stochastic variations and environmental noise, thereby providing a robust solution for autonomous decision-making in aerospace robotics [45]. This hybrid approach not only enhances the reliability of robotic systems operating in extraterrestrial conditions but also paves the way for more intelligent and context-aware systems capable of navigating the complexities of space exploration.

$$S\left(r_{\mathcal{D}}^{(L)} \mid \theta, \mathcal{H}\right) = \prod_{\delta \in \mathcal{D}} \left\{ \frac{1}{\sqrt{2\pi\sigma_{\varepsilon}^{2}}} \exp\left[-\frac{1}{4\sigma_{\varepsilon}^{2}} \left(u_{i;\delta}^{(L)} - f_i(x_\delta;\theta) \right)^2 \right] \right\}$$

In summary, this research establishes a transformative paradigm for aerospace robotic systems by integrating deep reinforcement learning with large language models. The proposed framework not only addresses the inherent challenges of space-based object manipulation but also sets a new benchmark for intelligent robotic systems in extraterrestrial exploration and operations.

4. Results

Preliminary results indicate that our proposed framework significantly enhances the multi-drone system's ability to identify and manipulate unknown payloads. Notably, the cooperative learning paradigm improves overall performance compared to singular drone operations. In the experiment part, we test 7 different object for our space module in grasping mission the the torque and force applied by the robot arm as shown in Fig. 2. The trajectory tracking for our multi-drone system in 3D space is shown in Fig.3. The tracking error compared with the other two popular machine learning methods is shown in Fig.4. The training results relative to the different episodes based on our deep learning part as shown in Table I.

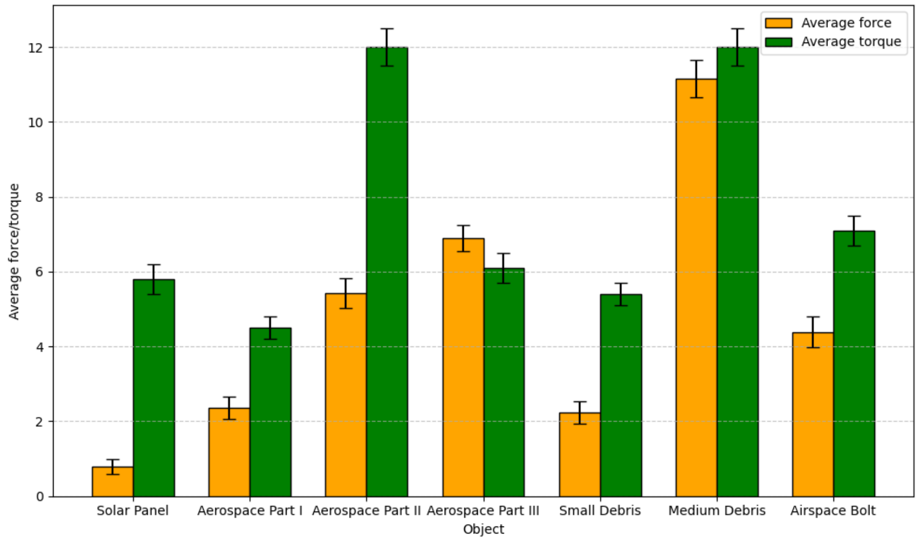

Figure 2. Loss value during the trainning process with our Deep Neural Network.

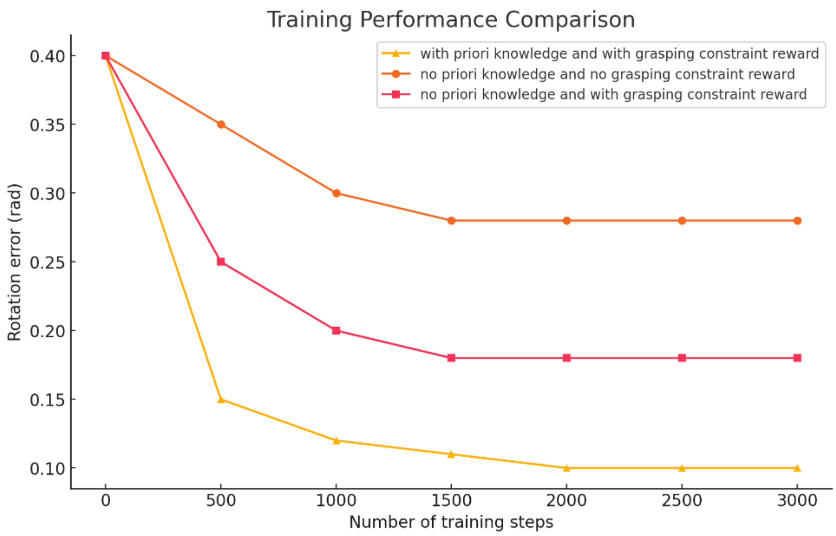

Figure 3. Trajectory tracking results for the end-effector of the robot arm on the space module in zero-gravity environment.

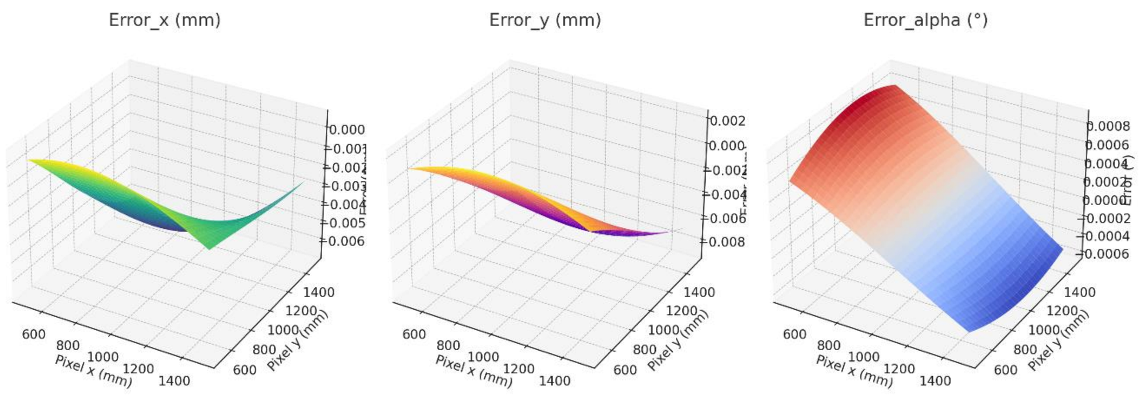

Figure 4. Transportation error for the base of the space module during the grasping task in space environment.

Table I: Accuracy of the grasping mission with deep learning.

Accuracy	100 Episodes	200 Episodes	300 Episodes	400 Episodes
Min	3%	24%	63%	93%
Max	22%	61%	89%	98%
Mean	12.5%	42.33%	76%	95.5%

5. Conclusion

This paper introduced a novel real-time whole-body obstacle avoidance framework tailored for multi-DoF redundant manipulators, with a particular focus on addressing challenges in dynamic environments. The proposed approach leverages a deformable dynamical system, where the original DS is adaptively modified through a combined modulation matrix accounting for the motion of surrounding obstacles. This deformation ensures that the end-effector can compute a trajectory capable of dynamically circumventing obstacles while achieving the desired target in real time. During trajectory tracking, null-space velocity control was employed to guarantee obstacle avoidance for the remaining non-end-effector components of the manipulator. By integrating deep learning into the framework, the system can further enhance adaptability, leveraging neural networks for real-time prediction of obstacle dynamics and optimizing control strategies in complex, high-dimensional spaces. The generalizability of the proposed approach allows its extension to manipulators with different degrees of freedom, making it particularly well-suited for applications in space environments, where precision, adaptability, and computational efficiency are paramount.

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