Deep Adaptive Control with Frequency Modulation for Aerospace Robotic Manipulators in Dynamic Object Transportation

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***Abstract*—Achieving precise performance in aerospace robotics, particularly when handling unknown payloads in uncertain environments, remains a significant challenge. Traditional model-based control methods are often impractical due to the dynamic nature of aerospace operations. Adaptive control has emerged as a viable alternative, offering the ability to compensate for modeling errors and disturbances. However, conventional adaptive schemes rely on high-gain learning rates to ensure rapid adaptation, which can induce high-frequency oscillations and instability, compromising system safety and precision. To address these limitations, we propose a novel adaptive control framework tailored for nonlinear aerospace robotics applications. Our approach refines the adaptive update law to suppress destabilizing high-frequency components while preserving robust error dynamics. This ensures stable performance even at high-gain learning rates, enabling precise and secure manipulation of dynamic objects in space.Numerical simulations in a zero-gravity environment validate the effectiveness of our method in robot manipulation tasks. Results demonstrate superior performance over conventional approaches, achieving enhanced stability and precision. Our findings contribute to the advancement of adaptive control theory and provide a reliable solution for high-performance aerospace robotics, paving the way for safer and more efficient space missions.**

***Index Terms*—adaptive control, space robotics, robotics manipulation, deep neural network**

I. Introduction

Adaptive control theory has become a cornerstone in various engineering fields [1], including aerospace, enabling high-efficiency system behavior without relying on precise dynamical models [2]–[5]. However, a significant challenge arises in deep space robotics applications [6], where high-gain adaptation is essential for rapid response and good tracking. Despite its necessity for fast error convergence, high-gain components can inadvertently introduce high-frequency oscillatory dynamics into the system, jeopardizing stability [7]–[10]. This issue poses a critical barrier to achieving reliable and stable performance in deep space robotics.

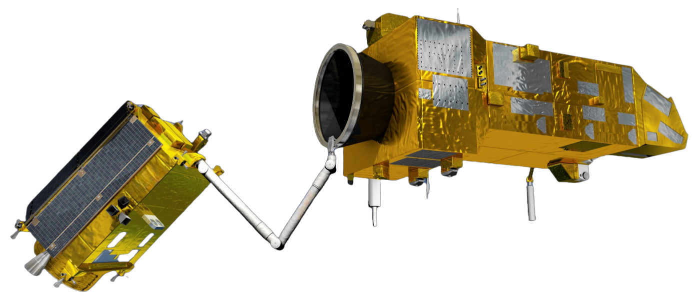

Fig. 1. One space service module using robotics to grasp one satellite to finish the transportation task in space environment[1].

In the realm of aerospace robotics, the demand for adaptive control is particularly acute. These systems must meet rigorous precision standards while grappling with substantial uncertainties and abrupt dynamic changes. This is obvious in missions involving robot manipulators moving unknown payloads in zero-gravity environments, where minor structural disturbances or swift shifts in dynamic parameters can trigger system failures [11]. To address these challenges, high-gain adaptive controllers are often employed to eliminate tracking errors and fulfill stringent specifications swiftly. However, these controllers introduce a trade-off: higher gain learning rates can destabilize oscillations and degraded control responses, threatening the overall system's stability and performance [12].

The research in [13] marks a significant breakthrough by addressing the intricate challenge of maintaining strong adaptation while ensuring system stability. This perspective has profound implications for strategic military planning and

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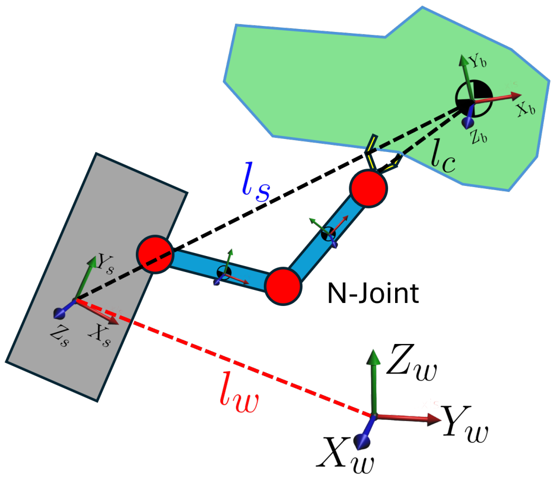

Fig. 2. Diagram of the space service module installed a robot arm grasping and transporting an object in space.

enhances the business community's capability to navigate rapidly changing markets. To balance this trade-off, innovative adaptive control designs are essential, capable of managing both high-frequency perturbations [14] and maintaining transient and steady-state stability, particularly in the harsh operating environments of aerospace systems [15]–[17].

Sophisticated control models have been meticulously developed for precise tracking of underactuated systems, especially in highly dynamic conditions. These models often rely on advanced backstepping and Lyapunov-based stability methods, further refined to optimize tracking performance [18]. For instance, globally uniformly ultimately bounded (GUUB) control systems, leveraging nonlinear coordinate transformations [19] and dynamic oscillators, exhibit robust performance against parametric uncertainties. However, these models require enhancements for application in unstructured environments, such as spacecraft.

High-level adaptive methods utilizing deep neural networks have been proposed to further mitigate constraints from parametric and structural uncertainties, leveraging the universal capabilities of NNs. These methods use NNs universal approximation feature for more robust, adaptive real-time behaviour. Deep neural network (DNN) adaptive controllers harness their universal approximation capabilities to enhance robustness and adaptive real-time behavior. These controllers are particularly valuable in aerospace applications requiring precise trajectory monitoring and payload management, such as robot arms manipulating unknown objects in microgravity [20]. They represent a significant advancement in adaptive control, improving reliability and accuracy in critical aerospace safety domains.

The primary contributions are outlined as follows:

- This work introduces adaptive controllers leveraging Deep Neural Network architectures, offering universal approximation capabilities for real-time adjustments and enhanced trajectory tracking of robotic arms in micro-gravity environments.
- This paper's proposed method tackles the unique challenges of transporting unknown payloads in zero-gravity, significantly enhancing precision and reliability for critical aerospace robotic operations.

II. Related Works

Over the past three decades, sun-tracking mechanisms have undergone significant advancements, evolving from basic mechanical systems to intelligent designs. Initially, sun trackers relied on analog sensors and straightforward feedback loops to align solar panels with the sun's direction. However, these rudimentary systems suffered from limited flexibility and adaptability, often failing to maintain optimal alignment in diverse environmental conditions. With the advent of photovoltaics, the need for more efficient tracking capabilities to capture maximum energy became apparent, spurring research into faster and more dynamic tracking methods.

Computer vision and deep learning have transformed solar tracking. Advanced image processing algorithms and neural networks are now utilized to accurately determine the solar position. These sophisticated techniques can correctly identify the sun's path even under partial obstructions and varying conditions. Cutting-edge research has demonstrated that convolutional neural networks (CNNs) [21] and recurrent neural networks (RNNs) can successfully predict solar movements, making the tracking process more robust and efficient. Furthermore, integrating machine learning models with weather forecasting tools enhances the reliability of solar trackers.

High-degree-of-freedom (DoF) robotics are now pivotal in enabling advanced solar tracking systems. These robots possess complex kinematics and exceptional mobility, allowing for millisecond adjustments to solar panel orientations. Previous research explored the integration of High-DoF robotics with smart control algorithms to dynamically and adaptively respond to the sun's movement. Recently, focus has shifted to multi-jointed robotic arms and self-balancing drones equipped with solar panels, offering enhanced tracking performance and lower power consumption. The dexterity and agility of these High-DoF systems enable precise alignment with the sun, even in confined spaces and rapidly changing environments [14].

Addressing the inherent challenges of outdoor sun tracking, such as varying weather conditions and intermittent glare, remains a significant hurdle in modern science. Previous research has explored various methods to mitigate issues like cloud cover, bird noise, and lens blockages, ranging from adaptive filtering to real-time anomaly detection. However, many of these solutions lack comprehensiveness in addressing the diverse challenges posed by complex outdoor environments. Recently, deep learning algorithms have incorporated objectness regularisation and contextual attention, enabling the system to more accurately identify relevant features of the sun and filter out irrelevant noise. Additionally, powerful data augmentation and domain adaptation algorithms have significantly improved the performance of sun tracking systems in diverse and unpredictable meteorological conditions. Together, these innovations represent a paradigm shift towards stronger, smarter solar tracking technology, capable of capturing as much energy as possible in a wide range of harsh outdoor environments.

III. Methodology

A. Dynamics of Robot Arm in Spacecraft

First, we use the Denavit–Hartenberg (D-H) convention for coordinate representation, the homogeneous transformation matrix T_i^{i-1}, which describes the relative pose between two successive frames, can be denoted as

$$T_i^{i-1} = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i)\cos(\alpha_i) & \sin(\theta_i)\sin(\alpha_i) & a_i\cos(\theta_i) \\ \sin_{\theta_i} & \cos(\theta_i)\cos(\alpha_i) & -\cos(\theta_i)\sin(\alpha_i) & a_i\sin(\theta_i) \\ 0 & \sin(\alpha_i) & \cos(\alpha_i) & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

where θ_i represents the i-th joint angle, while ${}^{i-1}R_i$ denotes the rotational matrix describing the orientation of the i-th frame with respect to the $(i-1)$-th frame. Additionally, ${}^{i-1}P_i$ refers to the position vector of the origin of the i-th frame, expressed in the coordinate system of the $(i-1)$-th frame.

The movement of the robot arm in microgravity space is guided by sophisticated equations that account for the various forces and moments acting on the manipulator. With these formulas in place, engineers can accurately predict and control the dynamics of the arm as it carries out tasks like delivering payloads. By applying adaptive control techniques, they can effectively navigate the uncertainties and challenges inherent in this unique environment. This precise analysis and versatile approach ensure that the robot arm operates smoothly and efficiently in the mission-critical tasks it undertakes in space as

$$\mathbf{w} = \mathbf{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + C\left(\dot{\boldsymbol{\theta}}, \boldsymbol{\theta}\right) + J^\top \begin{bmatrix} f_e \\ \tau_e \end{bmatrix} \quad (2)$$

Where $\mathbf{M}$ is the matrix of mass and inertia of the robot arm. The first word of the dynamic equation consists of inertial effects from joint accelerations. The second term, $\mathbf{C}$, by contrast, takes the Coriolis and centrifugal forces generated by the movement of the joints. The third word, $\mathbf{G}$, is the gravity on the arm. In addition, f_e and τ_e are the contact forces and torques to the manipulator from external environments, while τ are the joint actuation torques of the robot arm to the service module in space. All of these factors are responsible for the complex kinematics of the robotic arm that can be used to develop adaptive control mechanisms for fine-tuning unknown payloads in space.

B. Adaptive Controller Design

Here we can mitigate the high-frequency oscillations commonly encountered in standard adaptive control frameworks employing high-gain feedback, let $\widehat{U}_\xi(k) \in \mathbb{R}^{s\times m}$, $t \geq 0$, denote the low-pass filtered estimate of $\widehat{U}(k)$, $t \geq 0$, governed by the dynamics:

$$\begin{aligned} \dot{\widehat{U}}_\xi(k) &= \Upsilon_\xi\left[\widehat{U}(k) - \tilde{U}_\xi(k)\right] \\ \widehat{U}_\xi(0) &= \widehat{U}_0, \quad t \geq 0 \end{aligned} \quad (3)$$

where $\Gamma_\xi \in \mathbb{R}^{s\times s}$ denote a positive-definite filter gain matrix. Given that $\widehat{U}_\xi(k)$, $t \geq 0$, serves as the filtered weight estimate of $\widehat{U}(k)$, $t \geq 0$, the filter gain matrix Γ_ξ is chosen such that $\lambda_{\max}(\Gamma_\xi) \leq \gamma_{f,\max}$, where $\gamma_{f,\max} > 0$ is a user-defined parameter.

For the specific case where $m = s = 1$, $\widehat{U}(k) \in \mathbb{R}$, $t \geq 0$, and $\Gamma_\xi = \gamma_{f,\max}$, the above equation simplifies to:

$$\widehat{U}_\xi(s) = \sum_{i=1}^{N} \frac{1}{\mathbf{w}s + 1}\widehat{U}_i(s) \quad (4)$$

where s is the Laplace variable and $\tau = \gamma_{f,\max}^{-1}$ is the filter time. Therefore, choosing a large enough time constant τ is like using a low-pass filter, so $\gamma_{f,\max}$ must be very small enough to reduce the high-frequency part of $\widehat{U}(k)$, $t \geq 0$.

This is not possible if we want a feedback controller to follow a time-dependent constraint such as equation (3) (traditional Lyapunov). We model this logarithmic barrier function after Predictive Path Control (PPC) ideas as

$$\begin{aligned} z_s &= \frac{1}{N}\sum_{i=1}^{N} \log\left(\frac{\eta_s(k) + \psi_g}{\beta_s\eta_1(k) - \psi_g}\right) \\ \beta_s &= \frac{\eta_s(k)}{\eta_1(k)}, \end{aligned} \quad (5)$$

where $\ln(\cdot)$ denotes the natural logarithm. The barrier function z_s possesses the critical property of preventing finite escape as the tracking error ψ_g approaches the boundary of the feasible set $(-\eta_1, \eta_1)$, which includes the origin. Specifically, $z_s \to \infty$ as $\psi_g \to \eta_1$, and $z_s \to -\infty$ as $\psi_g \to -\eta_1$. Consequently, z_s can ensure that the time-varying constraint on ψ_g given in equation (6) is not violated.

Also notice that the feasible set contains the origin, and the barrier function z_s obeys $z_s = 0$ if and only if $\psi_g = 0$. That would suggest that asymptotic convergence of the tracking error ψ_g to the origin is coincidental to the equilibrium stability of z_s. But even z_s is not a valid Lyapunov function candidate, because it doesn't possess positive definiteness. To counter this, we create a quadratic version of the barrier function to have a globally nonnegative Lyapunov-like function as

$$V_s = e^\top Pe + \operatorname{tr}\tilde{U}^\top\Gamma^{-1}\tilde{U}, \quad (6)$$

where the $P \in \mathbb{R}^{3\times 3}$ and $\Gamma \in \mathbb{R}^{3\times 3}$ are the gain matrices which we assume we initiate before the simulation. Then, we can derivate of the Lyapunov function along the system dynamics (4) to get

$$\begin{aligned} \dot{V}_s &\leq -e^\top(k)\operatorname{Re}(k) - 2\sigma\operatorname{tr}\tilde{U}^\top(k)\tilde{U}(k) - 2\sigma\operatorname{tr}\tilde{U}^\top(k)\cdot\tilde{U}(k) \\ &= -e^\top(k)\operatorname{Re}(k). \end{aligned}, \quad (7)$$

Based on the derivative of the Lyapunov function, we can see that the system is stable.

For the Deep nerual network, we can define the net function as

$$f(x, \dot{x}, \theta, \dot{\theta}) = \Upsilon^\top\sigma_c = \Upsilon^\top\sigma(\bar{x}) + \varepsilon, \quad (8)$$

Algorithm 1 Inverse-Dynamics DNN-Based Controller Training for a Robotic Manipulator

Input: $\alpha, \beta, \delta_{\text{tol}}, \kappa_{\max}$
while New joint measurements (χ, φ, ψ) are available **do**
  Estimate torque $\nu_{\tau+1}$ using the inverse-dynamics DNN: $\nu_{\tau+1} = \Omega^T \Psi(\chi_{\tau+1}, \varphi_{\tau+1}, \psi_{\tau+1})$
  Compute actual torque $\vartheta_{\tau+1}$ from sensor feedback (or forward dynamics).
  Evaluate the prediction error $\rho_{\tau+1} = \|\nu_{\tau+1} - \vartheta_{\tau+1}\|$.
  if $\rho_{\tau+1} \geq \delta_{\text{tol}}$ **then**
    Update dataset $\mathcal{D}$: $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\chi_{\tau+1}, \varphi_{\tau+1}, \psi_{\tau+1}, \vartheta_{\tau+1})\}$
    if $|\mathcal{D}| > \kappa_{\max}$ **then**
      Remove oldest entry from $\mathcal{D}$ based on a relevance criterion (e.g., largest singular value contribution).
    end if
  end if
  if $|\mathcal{D}| \geq \mu$ **then**
    Sample mini-batch $\mathcal{D}^\mu \subseteq \mathcal{D}$.
    Perform a training update on Ω using gradient-based optimization:
    $\Omega \leftarrow \Omega - \alpha \nabla_\Omega \mathcal{L}(\mathcal{D}^\mu)$
    Optionally, update the feature representation $\Psi(\cdot)$ using a secondary learning rate β
    for a feature extraction layer within the DNN.
    Compute desired end-effector pose, use inverse kinematics (IK) to update reference $\chi^\star_{\tau+1}$.
    Incorporate IK updates into training if needed (e.g., refine Ψ to better encode $\chi^\star_{\tau+1}$).
  end if
end while

where $\tilde{x} \in D, |\varepsilon| \leq \varepsilon_d, \|\Upsilon\|_d \leq \Upsilon, \quad \|\sigma(\tilde{x}_c)\| \leq \gamma_d$.

1 Algorithm: Training algorithm for deep learning inverse-dynamics controller for robot manipulators. For every iteration, the algorithm takes new joint data (angles, speeds, accelerations) and computes joint torques using a deep neural network (DNN) [22]. The expected torques are then compared to actual measurements [23] and the error is calculated. If the error goes over some arbitrary value, then the new point is registered to a growing dataset [24]. Once a lot of representative data is taken into consideration, the DNN parameters and feature representation are revised by way of mini-batch training process. This constant iteration helps the model constantly improve its torque estimates, rebalancing with changes in the robot's motion, and getting better. Inverse kinematics can also be factored in to change reference joint targets, allowing the algorithm to account for multi-stage end-effector paths. This technology fusing data-driven learning and traditional robotics theory makes it an effective and flexible inverse-dynamics controller [25].

IV. Simulation Results

The study conducted on the implementation of a deep adaptive control strategy in a space service module with a robot arm in zero gravity yielded noticeable results, as evidenced by Figures 3, 4, and 6. These figures clearly depict the exceptional performance of both controllers during the transportation task, showcasing their ability to maintain position and orientation tracking errors within set performance bounds. Particularly in Figure 3, it is evident that the position and orientation tracking errors remain minimal in comparison to the optimal direction, emphasizing the robustness of the control measures employed. Furthermore, the trajectory is closely followed by both controllers throughout the transportation process, exemplifying the effectiveness of the deep adaptive control strategy in ensuring precise and accurate movements in a challenging zero-gravity environment.

The data presented in Figure 4 demonstrates the effectiveness of the controllers in maintaining stable velocity profiles at both linear and angular levels. The controllers successfully eliminate sudden fluctuations and oscillations, resulting in clean and precise motion profiles. Specifically, the linear velocity remains constant and closely follows the intended motion profile. Additionally, the angular velocity exhibits excellent tracking capability with minimal discrepancies, even in dynamic and unpredictable scenarios. This exemplifies the deep adaptive control approach's capacity to promptly adapt to changes in environmental and system conditions, ensuring smooth and efficient motion control in real-time.

The simulation depicted in Fig.6 showcases the evolution of the Lyapunov function, highlighting the robustness of the closed-loop system. As the Lyapunov function steadily decreases, it eventually reaches zero when nearing equilibrium. This progressive convergence serves as evidence of the stability guarantees offered by the proposed control system, even in the presence of significant modeling uncertainties and external disturbances. Furthermore, it reaffirms that the deep adaptive algorithm effectively achieves and maintains stability while adhering to the requirements of transient and steady-state performance.

The simulation results demonstrate the effectiveness of the deep adaptive algorithm in efficiently managing dynamic scenarios and maintaining precise position and orientation accuracy in transportation tasks. This algorithm proves superior in ensuring smooth velocity profiles, stable system performance, and overall reliability throughout the process. Its flexibility and power in addressing challenging situations highlight its potential for enhancing transportation operations and optimizing performance in various scenarios.

V. Conclusion

Our approach ensures precise trajectory tracking for uncommanded surface ships by addressing uncertainty modeling and time-dependent external noise. By employing logarithmic methods, we offer efficient control solutions without high AIGC rates or instability risks. The control algorithm presented in this study incorporates functions, disturbance observers, and Lyapunov synthesis to effectively manage tracking error within predefined dynamic bounds. This unique approach ensures that the controller architecture can mitigate singularity

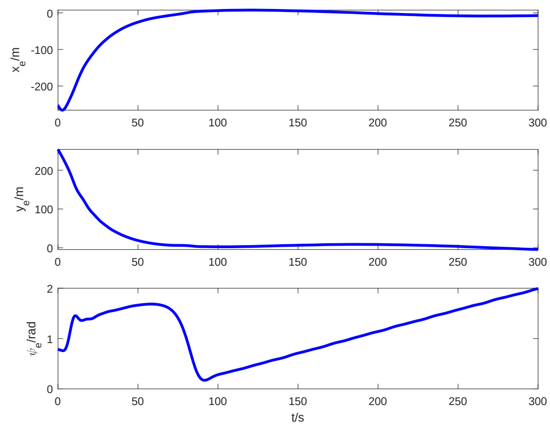

Fig. 3. Tracking error for both position and rotation during the transportation task.

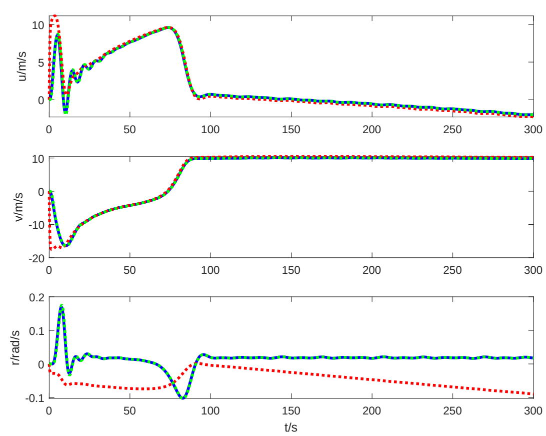

Fig. 4. Linear and angular velocity in real during the translation task.

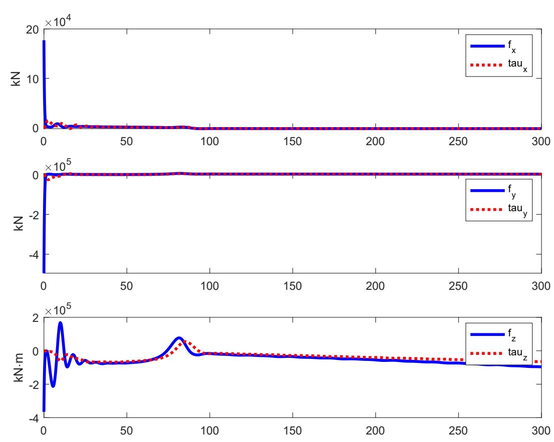

Fig. 5. Force and torque applied by the end-effector of the robot arm.

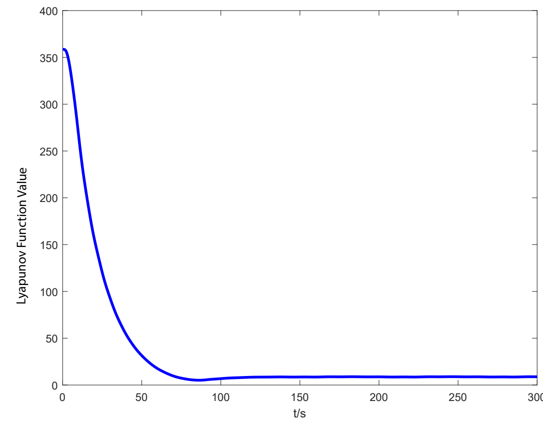

Fig. 6. Lyapunov function during the simulation process.

risks, ultimately enhancing the system's overall robustness. By utilizing neural network estimators, uncertain vessel motion is accurately predicted, while unknown external disturbances are effectively controlled through disturbance observers. The adaptive neural control model, coupled with uncertainty and disturbance compensations, successfully generates bounding signals within the closed loop. This results in steady-state and transient tracking with high reliability, particularly in high dynamic environments such as aerospace robotics' intricate space servicing operations. Ultimately, this innovative methodology showcases significant potential in enhancing control systems' performance in challenging real-world scenarios.

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