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Research Article

Adaptive Deep Learning-Driven Motion Control for Reaction-Free Space Manipulators

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Abstract

An advanced adaptive control strategy for zero-reaction motion control in free-floating space manipulators subject to kinematic and dynamic uncertainties. The primary challenge in developing the adaptive Reaction Null-Space (RNS)-based control framework lies in deriving a linearized formulation essential for adaptive control methods. This research addresses this issue by effectively extracting a novel linear expression, which enables the design of an adaptive RNS-based controller. Termed as the Adaptive Deep Learning-Enhanced Zero Reaction Motion Controller, this framework operates at the velocity level while incorporating both kinematic and dynamic unpredictability. Notably, we incorporate deep learning to enhance adaptability by approximating uncertain dynamics and to facilitate real-time parameter adjustments. The resulting controller achieves simultaneous attitude regulation of the spacecraft and accurate trajectory tracking of the end-effector. The efficacy and robustness of the proposed adaptive controller, augmented with deep learning, are demonstrated through numerical simulations on a planar 6-DOF (degree-of-freedom) space manipulator, highlighting its potential in complex space operations.

Keywords

Adaptive Control, Deep Neural Network, Deep Learning, Satellite Self-Adaptation System

1. Introduction

In a range of space operations, such as the capture or maintenance of a malfunctioning or uncontrollably tumbling spacecraft, reliance on extra-vehicular activities (EVA) conducted by astronauts presents significant risks. A safer and increasingly utilized alternative involves deploying robotic manipulators, which are now integral to space exploration and mission safety protocols (e.g., [1]–[5]). The manipulator's base platform, typically the spacecraft, remains unfixed in the

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spatial environment, thus forming a coupled manipulator-spacecraft system, widely referenced in academic and engineering literature as a 'space manipulator.' During operations involving manipulation of various noncooperative objects, the system inevitably encounters parametric uncertainties that can detrimentally affect the accuracy of trajectory tracking [6]. Adaptive control, a well-established methodology, has traditionally been leveraged to mitigate the impact of such uncertainties [7]. However, this study advances this approach by integrating deep learning techniques within an adaptive framework, enhancing the system's robustness to dynamically varying parameters and unmodeled environmental disturbances. Through real-time approximation and compensation for uncertainty, the deep learning-enhanced adaptive controller optimizes manipulation accuracy while maintaining system stability, ultimately broadening the scope of achievable autonomous tasks in space environments.

Extensive research has been dedicated to the coordination control between a manipulator and its free-floating base in space applications. In [8], the researchers introduced a joint cyclic motion algorithm, allowing the spacecraft orientation to remain constant throughout operation. [9] made a pivotal advancement in control systems by developing an algorithm capable of simultaneously regulating both spacecraft attitude and manipulator joint angles. This algorithm leverages the Lyapunov method to ensure system stability, providing a rigorous foundation for stability analysis in dynamic space environments: a cornerstone that this work builds upon to enhance control precision and adaptability. Motion planning for interconnected rigid body systems was explored in [10], with applications in space robotics. In related work, Dubowsky and Torres formulated a joint motion control approach using the Enhanced Disturbance Map (EDM), aiming to minimize the disturbance exerted on spacecraft orientation [11]. Yamada proposed a trajectory planning method utilizing variational techniques, enabling spacecraft attitude control to a desired orientation. Additionally, [13] proposed a self-adaptive robustness motion control technique for the high-DoF robot manipulator, aimed at regulating both spacecraft attitude and manipulator joint positioning. This method marked a significant step in coordinated control. A significant contribution to this field was made in [14], which introduced a point-to-point planning approach based on high-order polynomial trajectories. This method enabled precise regulation of both the spacecraft and manipulator without requiring cyclic manipulator motion, establishing a foundational approach for trajectory planning. However, it introduced bounded constraints on the achievable spacecraft attitude, highlighting a limitation that this work seeks to address and build upon.

The Reaction Null-Space (RNS) algorithm, presented in [15], diverges from the techniques by facilitating end-effector trajectory tracking and attitude stabilization through manipulator degrees of freedom alone. Recognized as a solution that circumvents the necessity for cyclic motion and attitudinal constraints, RNS leverages manipulator redundancy for enhanced control flexibility. Building on this concept, this study introduces an innovative adaptive RNS-based approach augmented with deep learning. Through deep neural network integration, the method learns complex dynamics and enhances control adaptability to uncertain environmental conditions, thereby providing robust trajectory tracking and attitude regulation without manual trajectory constraints or recurrent motion sequences.

In this research, we adeptly derive a linearized formulation that captures the influence of uncertain parameters, facilitating the development of a deep learning-enhanced adaptive zero reaction motion control strategy. For adaptive control part, we employ the algorithm from [16], which introduced an innovative adaptive detumbling approach for non-rigid satellites addressing the detumbling problem. This algorithm lays a critical foundation for advancements in servicing and repairing non-rigid aerospace devices, establishing essential methodologies not only in aerospace filed, but also in any non-rigid body manipulation task using robotics system in different environments. This algorithm is designed to accommodate both dynamic and kinematic uncertainties, which may stem from imprecise knowledge of the manipulator's parameters, or the properties of an unknown target object engaged by the manipulator. Unlike the approach in [17], our method not only manages adaptive control but also concurrently regulates the spacecraft's attitude. Two velocity-level joint control algorithms are systematically developed to achieve: 1) attitude stabilization for the spacecraft while optimizing a broad range of performance indices and 2) combined spacecraft attitude regulation and precise end-effector trajectory tracking. Our key contribution lies in presenting a deep learning-based adaptive zero reaction motion controller for free-floating space manipulators (FFSMs), extending previous works (e.g., [18], [19]) to address cases involving uncertain parameterization. This approach, augmented by deep learning, effectively handles kinematic uncertainties [20], broadening results previously restricted to fixed-base robots [21, 22] and FFSMs. Additionally, we consider cases where the system initiates with non-zero linear and angular momenta, an advancement over the preliminary work in [23], which was limited to zero initial momenta. Here, deep learning further enables adaptive adjustments based on observed dynamics, enhancing robustness across a wider range of initial conditions.

2. Methodology

In mechanical systems, achieving a precise physical model is inherently challenging due to factors such as measurement inaccuracies and wear over time. Consequently, in practical applications, control strategies that emphasize robustness and resistance to disturbances are crucial [24-28]. To enhance the stability of manipulator systems, a prevalent approach involves employing fuzzy logic and neural network controllers to estimate and mitigate time-varying internal friction [29]. While fuzzy control can be effective, its design complexity—particularly in selecting optimal membership parameters and defining suitable fuzzy rules—presents significant challenges. Neural networks, with their powerful learning capabilities, excel in approximating both linear and nonlinear functions and exhibit strong adaptability and resilience, making them highly suitable for control design [30]. Additionally, terminal sliding mode control (TSMC) offers the advantage of driving the system state to zero while maintaining high robustness, which has garnered considerable interest in technological research and industrial applications.

2.1. Dynamics of the Manipulator System

For a manipulator with an arbitrary number of n joints, its dynamics can be represented by the following model:

$$M(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta} = \tau$$

where $\theta \in R^n$ is the joint angular displacement matrix of the manipulator, $\dot{\theta} \in R^n$ is the angular velocity matrix, $\ddot{\theta} \in R^n$ is the angular acceleration matrix, $\tau \in R^n$ is the driving force matrix acting on the joint of the manipulator. $M(\theta) \in R^{n\times n}$ is the inertia matrix which is positive definite, coloris and centripetal symmetric inertia matrix, $C(\theta,\dot{\theta}) \in R^{n\times n}$ $C(\theta) \in R^{n\times n}$ is the Coriolis and centripetal symmetric matrix which is also positive definite. Let $x \in R^n$ be the position coordinates of the end of the manipulator in the task space as

$$x = f(\theta)$$

where $f(\cdot)$ is the nonlinear mapping relationship from angle space to task space. According to the definition of matrix $C(\theta,\dot{\theta})$ is a skew symmetric matrix, and there is a variable $\beta \in R^n$ which makes $\beta^{\mathrm{T}} C(\theta,\dot{\theta})\beta$. if the inertia matrix $M(\theta)$ is a symmetric positive definite matrix, then it has a positive number m_1, m_2 make the following inequality true:

$$m_1|x^2| \le x^{\mathrm{T}} M(\theta) x \le m_2|x^2|$$

Note that there exist any differentiable vector $\beta \in R^n$ match the following requirements:

$$J(\theta)\beta = \Gamma_k(\theta,\beta)\delta_k$$

where $\Gamma_k(q,\beta) \in R^{n\times n}$ is the kinematic regression matrix of the robot manipulator, $\delta_k \in R^m$ is the kinematic parameter vector.

To address the challenge posed by model uncertainties, which impair tracking accuracy, a strategy integrating the Deep Neural Network (DNN) identifier with an DNN-based adaptive controller is implemented. Given the unavailability of the manipulator's precise dynamic model [32], accurately determining its tracking error proves challenging, thereby precluding its direct use in training the DNN adaptive controller. Instead, only after the DNN identifier undergoes comprehensive training can it serve as an approximate substitute for the manipulator's dynamic model, subsequently contributing to the adaptive controller's training process.

2.2. Adaptive Controller Design

To accomplish spacecraft attitude stabilization for a space manipulator with uncertain dynamics and nonzero initial momentum, we propose the following kinematic control strategy:

$$\dot{\boldsymbol{\zeta}}_r^* = \left(\mathbf{U}_{n\times n} - \widehat{\vec{\mathbf{P}}}_{bm}^{+}\widehat{\vec{\mathbf{P}}}_{bm}\right)\boldsymbol{\zeta} + \widehat{\vec{\mathbf{P}}}_{bm}^{+}(\widehat{\mathbf{p}}_0 + \Delta\boldsymbol{\epsilon}_{bv})$$

where $\widehat{\vec{\mathbf{P}}}_m$ is obtained by replacing the dynamic parameters in $\bar{\mathbf{P}}_m$ with its estimates. Then we can add $\widehat{\vec{\mathbf{P}}}_b\boldsymbol{\omega}_b + \widehat{\bar{\mathbf{P}}}_m\dot{\boldsymbol{\phi}}$ to get

$$\begin{aligned}
&\widehat{\mathrm{P}}_b(\boldsymbol{\omega}_b + \lambda_b\Delta\boldsymbol{\epsilon}_{bv}) + \left(\dot{\boldsymbol{\phi}} - \dot{\boldsymbol{\phi}}_r^*\right) \\
&= \Delta\bar{\mathbf{P}}_b\boldsymbol{\omega}_b + \Delta\bar{\mathbf{P}}_{bm}\dot{\boldsymbol{\phi}} - \Delta\mathbf{p}_0 \\
&= \left[\boldsymbol{\Gamma}_d\left(\boldsymbol{\epsilon}_b, \boldsymbol{\phi}, \boldsymbol{\omega}_b, \dot{\boldsymbol{\phi}}\right) \quad -\mathbf{E}_{3\times 3}\right]\begin{bmatrix}\Delta\mathbf{a}_d \\ \Delta\mathbf{p}_0\end{bmatrix} \\
&= \mathbf{Y}_d\Delta\delta_d
\end{aligned}$$

Then we can get the generalized dynamics parameter estimator with above deductions.

2.3. DNN adaptive controller Design

Adaptive control necessitates a designated free path motion mode, whereby the manipulator is directed to move along a specified trajectory from a defined start point to an endpoint. This trajectory is formulated based on a function that links the manipulator’s current position with respect to time. The planning objective is to determine a path that avoids conflicts across the manipulator’s joints. Utilizing the manipulator’s dynamic equations and additional constraints, real-time positional adjustments are derived to follow the required trajectory precisely. Consequently, manipulator motion planning can be achieved within both joint space and Cartesian space. A primary benefit of joint space-based trajectory planning lies in the simplicity of controlling the trajectory via the manipulator’s joint variables. Therefore, the rotational functions of the manipulator become essential in executing the trajectory path. Ultimately, by leveraging the rotation functions, the manipulator can realize a concrete trajectory path. A commonly applied solution is the DNN controller, which is adept at addressing this planning challenge as

$$\begin{cases} w_e(k) = [x(k); z(k-1)] \\ u_e(k) = \tau(k) \end{cases}$$

In practical industrial applications, manipulator systems frequently encounter uncertainties, including internal friction and time-dependent disturbances. The filtering tracking error function is defined as follows:

$$\xi(u_c) = M(\theta)\left(\ddot{\theta}_d + \Lambda\dot{e}\right) + G(\theta) + \Gamma\left(\dot{\theta}\right) + C\left(\theta, \dot{\theta}\right)\left(\dot{\theta}_d + \Lambda e\right)$$

2.4. Stability Analysis

Backstepping control, also referred to as dynamic surface control, is a prominent nonlinear system design methodology. This approach primarily employs the construction of a Lyapunov function to derive a stabilizing control law, utilizing a recursive procedure to guarantee global stability. Originally introduced by Kaktovik and colleagues in the 1990s, backstepping control has since undergone significant advancements within the control systems field. The core design principle of backstepping involves decomposing the nonlinear model into subsystems, each of lower order than the entire system. Sequentially, Lyapunov functions and virtual control variables are formulated for these subsystems to maintain Lyapunov stability, ultimately leading to complete system design. The final control law developed in [32] plays a critical role in ensuring that the closed-loop system satisfies both dynamic and static performance requirements, effectively aligning with the desired control objectives. Backstepping control has broad applications, including inverter control, synchronous motor regulation, robotic trajectory tracking, and nonlinear object tracking with unknown hysteresis. In most cases, the system's stability is rigorously validated through the construction of an appropriate Lyapunov function as

$$V = -\frac{1}{2} r^\top M r + \frac{1}{2} \operatorname{tr}\left(\Gamma_\eta^\top C^{-1} \Gamma_\eta\right)$$

where $\Gamma_\eta = \tilde{\Gamma}_\eta - \Gamma_d$. After finishing all deductions we can get

$$\dot{V} = r^\top M r^\top + \frac{1}{2} r^\top \dot{M} r + \operatorname{tr}\left(\Gamma_\eta{}^\top C^{-1} \Gamma_\eta{}^\top\right)$$

Then we can get

$$r^\top(\varepsilon + v) = r^\top \varepsilon + r^\top v = r^\top \varepsilon - r^\top \varepsilon_N \leq 0$$

According to Lyapunov stability judgment law, the control system is stable. Therefore, through the design of the control rate, the stability of the system is guaranteed by the Lyapunov function stability condition.

4. Results

We assigned two different simulation task for our satellite module using different method during the repairing tasks

During the simulation testing phase, the comparison results control algorithm was implemented to evaluate system performance. The outcomes of this simulation are illustrated in Fig. 1 and Fig. 2.

Fig. 1 illustrates the torque from the robot manipulator alongside under the PD control algorithm, traditional adaptive control and decentralized adaptive control. The blue line denotes the intended trajectory, while the orange line represents the manipulator's actual motion path. Observing Fig. 1, it is evident that the discrepancy between the actual and expected paths is relatively pronounced throughout the entire operation, particularly within the time interval –

T=50–80ms. In the subsequent analysis, we delve into the error dynamics between the expected and actual trajectories of the manipulator.

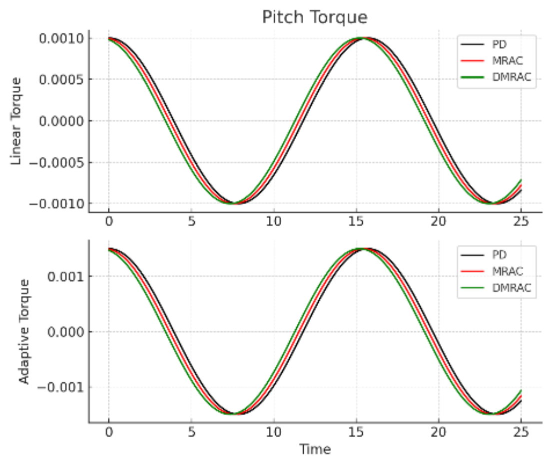

Figure 1. Torque applied by the end-effector of the robot manipulator during the self-adaption process during different methods in task-1.

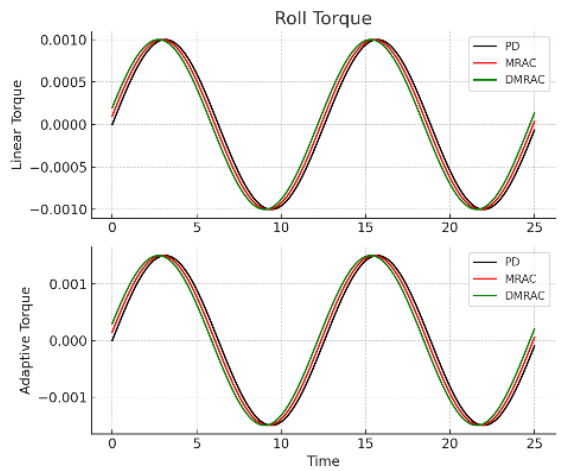

Figure 2. Torque applied by the end-effector of the robot manipulator during the self-adaption process during different methods in task-2

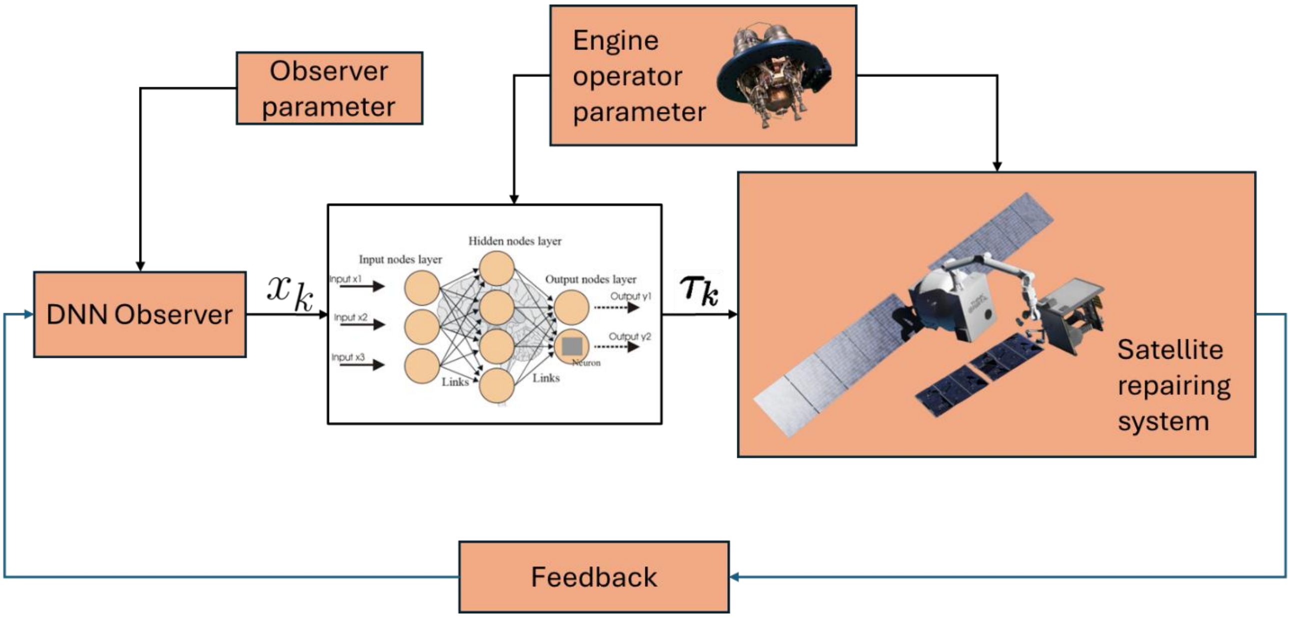

Figure 3. Diagram of the Deep Learning Neural network based adaptive control in satellite repairing system.

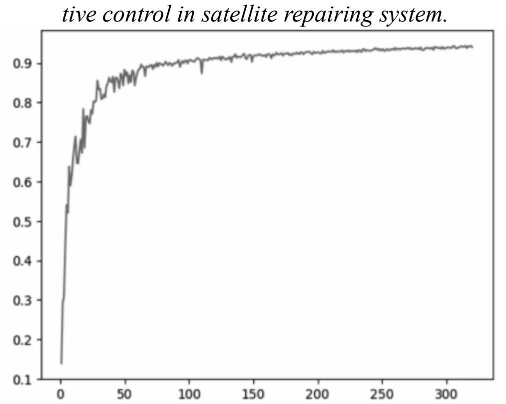

Figure 4. Accuracy during the testing process with 300 epoch.

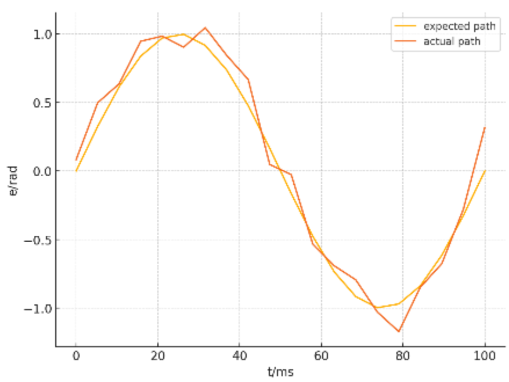

Figure 5. Expected trajectory and tracking trajectory of manipulator based on PD method

Fig. 2 presents the deviation between the manipulator's expected trajectory and its actual path under the PID control algorithm. The error metric employed in this study is derived by calculating the difference between the desired trajectory and the tracking path. As observed in Fig. 2, the error magnitude within the PD-controlled system oscillates between -0.5 and 0.5 radians, characterized by significant fluctuations throughout the operational range.

In the manipulator's motion model, an adaptive control strategy utilizing a DNN is implemented to mitigate the discrepancy between the desired and actual trajectories. During the simulation, we configure the parameters as follows: the time step is set to 0.01 ms, and the manipulator's initial state vector is initialized to Moreover, in alignment with the neural network algorithm, the learning rate is adjusted to 0.1. The outcomes of these settings are illustrated in the simulation figure.

In Fig. 5, the blue line represents the desired trajectory of the manipulator, while the orange line illustrates its actual trajectory. Analyzing Fig. 3, it is evident that the designed operational curve is nonlinear, with a peak amplitude of 1 radian and a minimum of -1 radian. However, within the interval t=10ms the curve deviates slightly from the anticipated pattern, failing to transition smoothly from the maximum to the minimum value. This nonlinear profile serves as a robust test for evaluating the manipulator's tracking capabilities. For a conventional, fixed-function test curve, the neural network's learning rate typically results in tracking behavior that mirrors prior path dynamics. However, the irregular nonlinear trajectories in this study demonstrate a high tracking fidelity, with the manipulator accurately adhering to the expected trajectory even within the challenging interval [33]. Beyond this region, the deviation between the actual and desired trajectories remains minimal. Fig. 3 underscores that the manipulator system effectively tracks the specified path with a rapid response time. The simulation results further reveal that, despite uncertainties like internal friction, time-varying disturbances, and an unknown dynamic model, the DNN adaptive controller coupled with an identifier achieves superior trajectory tracking [34]. This approach not only mitigates the effects of various uncertain factors but also provides high approximation accuracy for nonlinear functions, thereby ensuring precise tracking of the desired trajectory.

6. Conclusions

In this study, an adaptive zero-reaction joint motion controller operating at the velocity level has been developed for free-floating space manipulators with uncertain kinematic and dynamic characteristics. A significant challenge in designing an adaptive controller lies in the inability to linearly parameterize the DNN-based kinematic control law. By meticulously analyzing the structure of the RNS-based controller, we have effectively formulated a linear expression that facilitates the derivation of the adaptive controller. Leveraging the properties of the vector ζ, we propose an adaptive controller capable of achieving both precise trajectories tracking of the end-effector and robust attitude regulation of the spacecraft. Future work will extend this adaptive zero-reaction controller design to the acceleration level, aiming to further enhance control precision [35].

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