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DEEP LEARNING-DRIVEN REAL-TIME WHOLE BODY OBSTACLE AVOIDANCE FOR MULTI-DOF REDUNDANT MANIPULATOR IN SPACE

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1. Introduction

Redundant serial manipulators have found extensive utility in diverse domains, including industrial automation, precision manufacturing, and service robotics, due to their exceptional dexterity and adaptability. In operational scenarios, such manipulators are frequently required to navigate complex environments populated with dynamic entities, such as human operators, cooperative robotic systems, and other autonomous agents. These entities, collectively considered obstacles, may exhibit stationary or non-stationary characteristics, further complicating motion planning. In extraterrestrial environments, such as space missions [1], the manipulators face additional constraints [2], including microgravity and limited computational resources, necessitating advanced methodologies for collision avoidance. The integration of deep learning algorithms enables predictive modeling of obstacle trajectories, facilitating anticipatory and adaptive motion strategies. Ensuring collision-free operation across the entire manipulator structure is critical for task execution [3], such as object manipulation or assembly in microgravity. Consequently, real-time whole-body obstacle avoidance is indispensable for redundant manipulators to maintain operational efficacy in such challenging and dynamic contexts.

To address the intricate challenge of obstacle avoidance in robotic systems, an array of methodologies has been developed over the years. Broadly, these techniques can be categorized into reactive motion generation frameworks and trajectory planning paradigms. Trajectory planning approaches, exemplified in works such as [4], leverage sophisticated planning algorithms to circumvent obstacles. Nevertheless, the computational complexity associated with these methods imposes significant constraints, rendering them impractical for real-time applications, particularly in scenarios requiring instantaneous decision-making. [5] come up with a novel self-adaptive algorithm for robots to adapt itself in various external environment, which pave the foundation of self-adaption in robotics and can be extended in space reparing missions. This limitation becomes even more pronounced in space environments, where real-time obstacle avoidance must contend with additional challenges such as microgravity dynamics and constrained onboard computational resources. By integrating deep learning techniques, predictive obstacle modeling and adaptive motion strategies can be realized, significantly mitigating the computational burden and enabling seamless real-time operation in such highly dynamic and resource-constrained domains.

Reactive motion generation methodologies have been developed as an alternative to path planning approaches to facilitate real-time obstacle avoidance. Techniques such as the vector field histogram [6] and the curvature-velocity method [7] enable rapid evasion of obstacles. However, these methods often yield locally optimal solutions and cannot always guarantee a globally feasible trajectory. A groundbreaking decentralized adaptive control method for space robotic systems was proposed by [8], addressing the critical challenges of space servicing and repair under the uncertainty of aerospace accessories on satellites or spacecraft. This work represents a significant milestone in the development of adaptive servicing strategies, laying a robust foundation for tackling complex tasks in unstructured and unpredictable space environments. Notable advancements include the attractor dynamics approach in [9] and dynamic potential fields proposed by [10], among others. The APF method models obstacles as sources of repulsive forces, designed to repel the system away from collisions. However, these forces must be carefully defined to avoid local minima, a common limitation of APF methods.

To address the local minima issue, a novel monte Carlo tree search approach in [11] was introduced, combining reactive techniques with path planning algorithms to ensure collision-free navigation. The harmonic potential method [12] emerged as another widely adopted alternative [13], leveraging harmonic potential functions to mitigate local minima challenges. Inspired by fluid dynamics around impenetrable barriers, a novel dynamical systems (DS)-based method was proposed in [14]. This approach employs a modulation matrix for obstacles, deforming the original DS to compute an alternative trajectory that circumvents obstacles. Despite its efficacy, the DS-based method is inherently limited to convex obstacles. Extensions by Huber et al. [15] enabled the avoidance of concave obstacles, albeit restricted to linear DS, thereby limiting applicability to nonlinear dynamical systems.

In more recent developments, sensor-based obstacle representations, such as point clouds, have been incorporated into DS-based approaches [16], enabling adaptive and environment-aware obstacle avoidance. However, these methods face significant challenges in complex environments like space, where the dynamic and computational constraints demand more sophisticated solutions. By integrating deep learning, these reactive motion generation approaches can leverage neural networks to predict obstacle dynamics and adaptively optimize trajectories, offering a pathway to overcome limitations associated with nonlinearity, local minimum, and real-time performance in resource-constrained domains such as extraterrestrial environments.

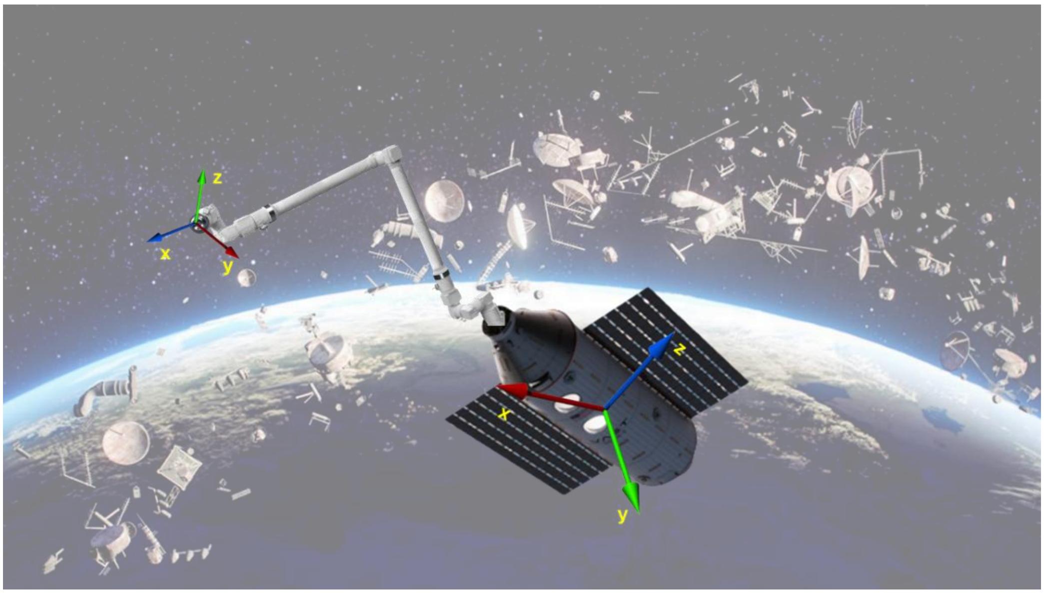

Figure 1. A Space module install a multi-dof robot arm in space environment.

2. Related Work

Obstacle avoidance strategies for redundant manipulators have been extensively investigated in the literature [17]. Numerous methodologies leverage null-space velocity control, wherein a velocity vector directed away from the obstacle is assigned to the manipulator's point of closest proximity to the obstacle [**18**]. Additionally, task-priority frameworks [19] have been proposed, which prioritize the execution of primary objectives, such as obstacle avoidance, only when deemed necessary. While these approaches offer computational efficiency, they are inherently constrained by certain simplifying assumptions, namely, that the manipulator's end-effector follows a predetermined global trajectory and that obstacles remain static. These limitations render such methodologies unsuitable for executing complex tasks, such as dynamically grasping objects in environments with multiple moving obstacles.

In the context of extraterrestrial operations, such as those encountered in space robotics, the complexities escalate further due to the presence of microgravity and rapidly changing obstacle dynamics. To overcome these challenges, deep learning paradigms can be integrated into null-space and task-priority frameworks to enhance their adaptability. By leveraging neural networks, the system can predict obstacle motion trajectories and dynamically adjust the end-effector's path in real time. This fusion of deep learning with classical control strategies enables manipulators to handle more sophisticated scenarios, such as interacting with multiple non-stationary obstacles, while maintaining compliance with mission-critical constraints in space environments.

As discussed previously, while numerous advanced obstacle avoidance techniques have been proposed, only a limited number of them can guarantee real-time whole-body obstacle avoidance (RWOA) for redundant manipulators, particularly when encountering moving obstacles during task execution. Certain approaches, such as those outlined in [20-22], are specifically tailored for obstacle avoidance at the manipulator's end-effector, whereas other methods, including those described in [23], address avoidance for the non-end-effector components—essentially the manipulator's body excluding the end-effector [24]. Moreover, many of these methods operate under the simplifying assumption that obstacles remain stationary, rendering them unsuitable for dynamic and highly unpredictable environments.

To address the RWOA challenge comprehensively, this study introduces a novel framework that combines dynamical systems (DS) with null-space velocity control. The proposed methodology is specifically designed to handle real-time obstacle avoidance across the entirety of a manipulator's structure, ensuring collision-free motion in the presence of moving obstacles. Given the widespread deployment of 7-DOF redundant manipulators in both terrestrial and extraterrestrial applications, this work focuses on manipulators with such configurations. Additionally, by incorporating deep learning into the DS-based framework, the proposed approach leverages neural networks for obstacle trajectory prediction, enabling anticipatory adjustments and adaptive control. This integration enhances the method's applicability to complex environments, such as space missions, where dynamic obstacles, microgravity conditions, and computational constraints pose significant challenges to traditional control strategies..

3. Methodology

In this study, we assume the presence of N discrete, dynamically moving convex obstacles surrounding the manipulator. Considering that manipulators predominantly operate within the Cartesian space, the obstacles under consideration are modeled as three-dimensional entities. In scenarios involving interconnected obstacles, they can be approximated collectively as a singular convex obstacle, as discussed in [25-29]. While non-convex objects, such as brushes or lamps, are frequently encountered in practical applications, a Bounding Volume (BV) approach [30] can be employed to encapsulate these irregular shapes within three-dimensional convex envelopes. This abstraction not only simplifies the computational complexity but also ensures that obstacle representations remain compatible with existing motion planning algorithms. To enhance adaptability in dynamic and space-specific environments, deep learning algorithms can be incorporated to predict obstacle motion patterns and refine the generation of convex representations in real time, thereby facilitating collision-free manipulator operation under complex spatial constraints.

The Newton-Euler formalism is utilized to derive the dynamic model of the space robotic system [31]. This methodology enables a comprehensive and intuitive analysis of forces and moments acting on the system and can be effectively extended to complex systems that incorporate closed-loop geometric constraints. The resulting dynamic equations account for the intricate interactions between the robotic links and the spacecraft base, providing a detailed representation of the system’s behavior under external and internal forces. By integrating deep learning techniques, the predictive capabilities of the dynamic model can be enhanced, allowing for real-time adaptation to dynamic environments and unforeseen disturbances, which are critical in space missions characterized by microgravity and constrained computational resources. The equations governing the dynamics of the robotic links and the spacecraft base are presented as follows:

$$
\begin{aligned}
&\boldsymbol{F}_N + f_{N-1,N} = m_N \dot{v}_N \\
&\tau_N + (-a_N) \times f_{N-1,N} + b_N \times F_N = \dot{H}_N \\
&f_{i-1,i} + f_{i+1,i} = m_i \dot{v}_i
\end{aligned}
$$

To develop controllers capable of tracking desired trajectories within the task space, it is essential to reformulate the dynamic equations of the space robot in terms of the task space control variables [32]. This transformation ensures that the control inputs are directly aligned with the task space objectives, facilitating precise trajectory tracking. Based on the above equation, the second-order derivative of the task space variable:

$$
\boldsymbol{n}_k(\tilde{\boldsymbol{\xi}}_k) = \begin{bmatrix} \frac{\partial \Gamma_k(\tilde{\boldsymbol{\xi}}_k)}{\partial(\boldsymbol{\xi}_1} & \frac{\partial \Gamma_k(\tilde{\boldsymbol{\xi}}_k)}{\partial(\boldsymbol{\xi})_2} & \frac{\partial \Gamma_k(\tilde{\xi}_k)}{\partial(\xi)_3} \end{bmatrix}^T
$$

the combined modulation matrix as

$$
\begin{cases}
\boldsymbol{S}(t) = \int_0^t \mathrm{e}^{-\delta(t-r)} \boldsymbol{Y}^T \boldsymbol{Y} \mathrm{d}r \\
\mathrm{W}(t) = \int_0^t \mathrm{e}^{-\delta(t-r)} \boldsymbol{Y}^T \boldsymbol{\tau} \mathrm{d}\boldsymbol{r} \\
\boldsymbol{T}(t) = \left[\mathrm{e}^{-t} \boldsymbol{U}_0 + \int_0^t \mathrm{e}^{t-r} \boldsymbol{I} \boldsymbol{L}^T \boldsymbol{L} \mathrm{d}r \right]^{-2} = [\mathrm{e}^t \boldsymbol{U}_0 + \boldsymbol{O}(t)]^{-2}
\end{cases}
$$

To further smooth the motion of obstacle avoidance, a smoothing factor h □ is presented in [18] to smoothly apply the homogenous solution as

$$
\frac{\partial \rho_a U_a}{\partial t} + \frac{\partial}{\partial x_j}\left(\rho_a U_{a_i} U_{a_j}\right) = -\frac{\partial \rho_a}{\partial x_i} + \frac{\partial}{\partial x_j}\left(\tau - \rho_a U_{a_i} \bar{U}_{a_j}\right) + S_{MOM}
$$

Then we incorporate the Deep Learning algorithm based on the dynamics of the space robotics system. The proposed GG-CNN framework offers two significant advantages over conventional state-of-the-art grasp synthesis convolutional neural networks (CNNs). First, instead of relying on sampling discrete grasp candidates, it generates grasp poses at a granular, pixel-by-pixel resolution [33]. This approach parallels advancements in object detection, where fully convolutional architectures are utilized to achieve pixel-wise semantic segmentation, superseding traditional methods like sliding windows or bounding boxes [34]. Such precision is particularly advantageous in space environments, where fine manipulation and accurate grasping are critical for handling delicate payloads and performing intricate tasks [35]. Second, the GG-CNN architecture is highly efficient, possessing significantly fewer parameters than its counterparts, which facilitates rapid closed-loop grasping operations. This efficiency is essential for resource-constrained environments, such as space missions, where computational power is often limited. Impressively, the grasp detection pipeline achieves execution times as low as 19 milliseconds on a GPU-enabled desktop system, enabling real-time performance in scenarios demanding high precision and adaptability. Incorporating deep learning methodologies into this framework further enhances its predictive and adaptive capabilities [36], making it ideal for dynamic and unpredictable extraterrestrial operations. The network equation can be expressed by

$$R_{\Theta}(I) = (Q_{\Theta}; \varphi_{\Theta}; B_{\Theta}).$$

where the grasp map G estimates the parameters of a set of grasps, for each Cartesian point in the 3D space corresponding to each pixel in the captured image. It constitutes asset of 3 images denoted as, Q, φ, and W.

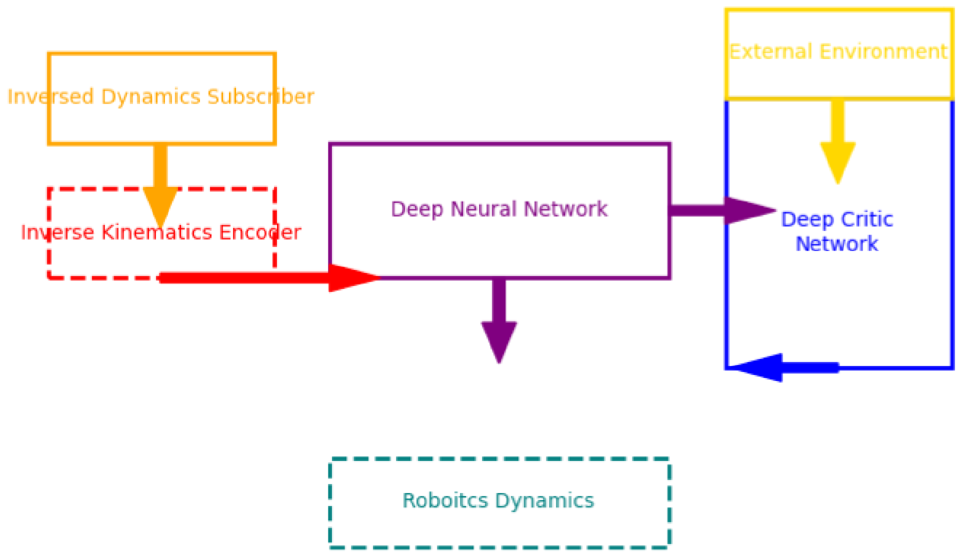

Figure 2. Algorithm design with Deep Neural Network for space module.

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. The trajectory tracking for our multi-drone system in 3D space is shown in Fig.4. The tracking error compared with the other two popular machine learning methods is shown in Fig.5.

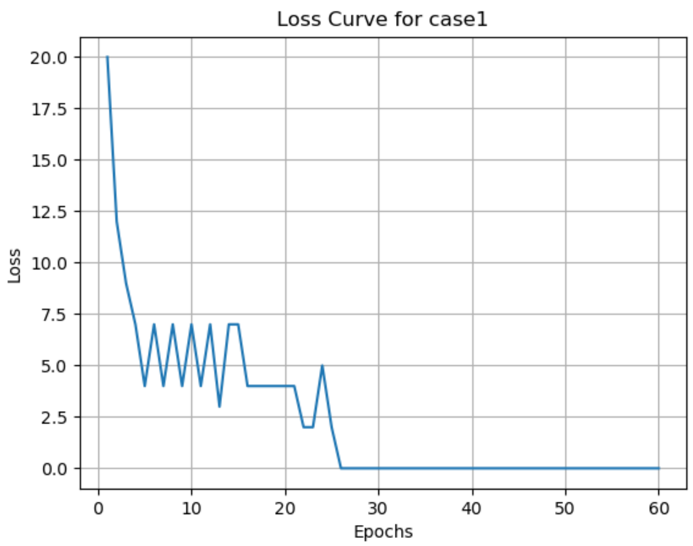

Figure 4. Loss value during the trainning process with our Deep Neural Network.

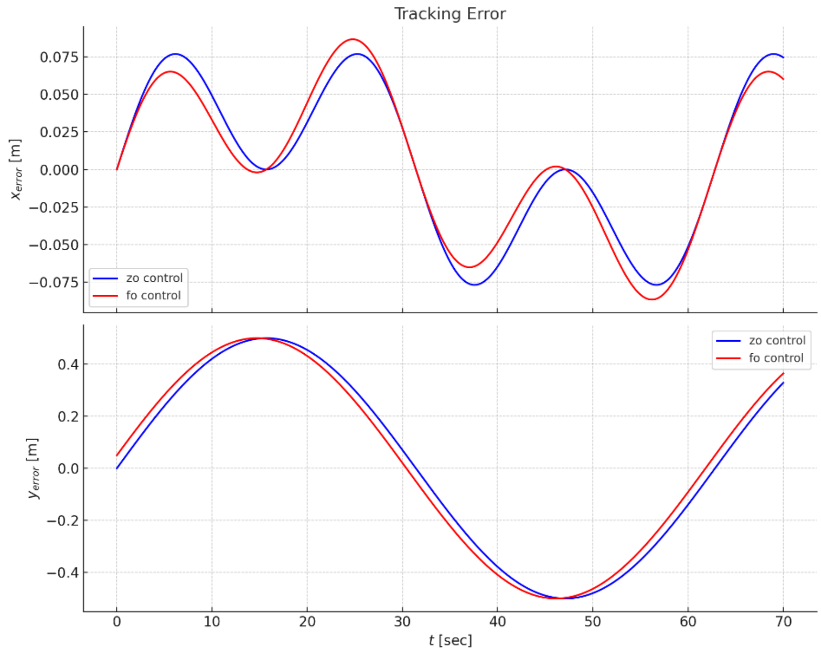

Figure 4. Trajectory tracking results for the end-effector of the robot arm on the space module in zero-gravity environment.

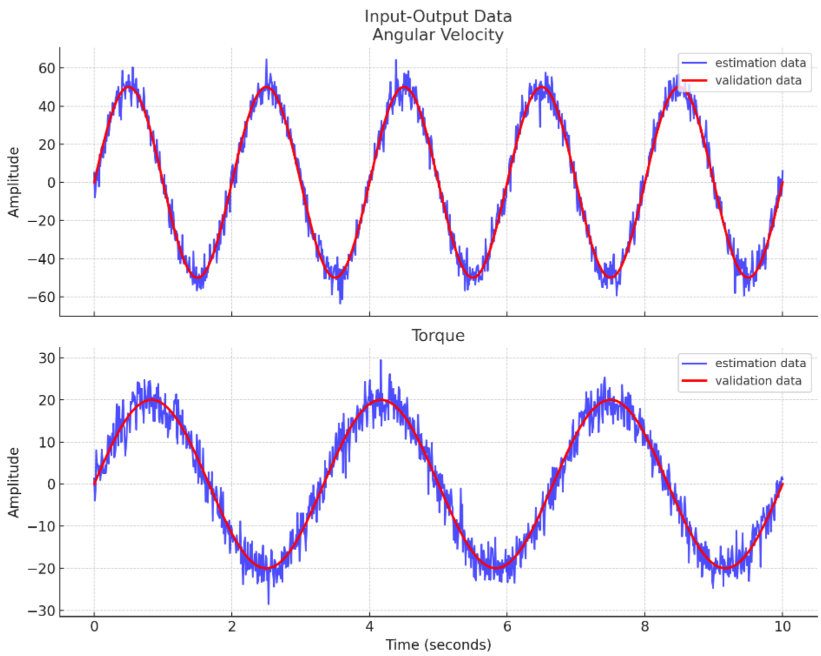

Figure 5. Amplitude of the base of the space module during the manipulation task in zero-gravity environment.

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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