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9.3 Pedagogy multi-drone system manipulation of unknown object using deep learning

9.3.1 Introduction

Over the past decade, unmanned aerial vehicles (UAVs)—commonly known as drones—have gained widespread attention in various sectors, including agriculture, delivery services, disaster management, and military applications [366-369]. The capability to autonomously manipulate payloads expands the functionality of drones significantly. However, manipulating unknown payloads presents unique challenges that demand sophisticated solutions. This paper focuses on a multi-drone system's ability to intelligently perceive and manipulate unknown payloads using advanced deep-learning algorithms [370]. The motivations behind this research stem from the increasing need for autonomous systems capable of efficiently performing tasks in unpredictable environments [371-373].

One of the most significant advantages of multi-drone systems is their enhanced coordination and efficiency. The ability for multiple drones to work in tandem allows them to cover larger areas more effectively than a single drone could manage alone. For instance, in aerospace applications, a fleet of drones can simultaneously monitor vast fields, gathering data on crop health [374], soil conditions, and pest infestations in real time. This collective effort not only enriches data collection but also minimizes the time taken to achieve comprehensive monitoring, thus empowering agent to make timely interventions that can enhance yields [375]. Furthermore, deep learning algorithms can optimize the flight paths of multiple drones, leading to reduced fuel consumption and longer operational durations. By analyzing historical data and real-time conditions, these algorithms can calculate the most efficient routes and adjust them dynamically, all while considering factors such as wind patterns and battery life [376]. This optimization is crucial in emergency scenarios, where time is of the essence. Improved communication between drones enables them to instantly share data, leading to faster response times in emergencies, such as natural disasters or search and rescue missions. For example, a coordinated multi-drone response can quickly cover and assess extensive disaster-struck areas, providing critical situational awareness to first responders. Hence, integrating deep learning in multi-drone systems significantly enhances their operational efficiency and effectiveness, ultimately leading to better outcomes across various applications[377-380].

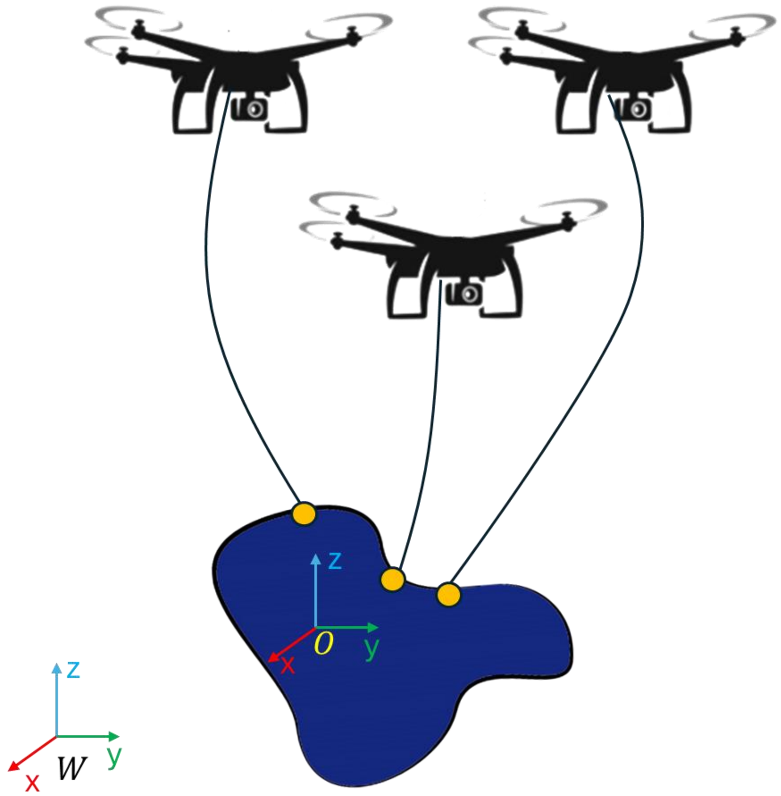

Figure 1. Multi-drone system lift object to transport to a target place.

9.3.2 Related Work

Building upon previous research in single-drone manipulation systems, where the payloads are typically known beforehand, much of the work has centered around model predictive control (MPC) and heuristic algorithms. These approaches have demonstrated effectiveness in controlled environments, but their adaptability to scenarios involving unknown or dynamic payloads is limited. As drones transition from single-agent systems to more complex multi-agent configurations, the challenges associated with cooperative payload manipulation become increasingly pronounced.

Multi-drone systems have been extensively studied for tasks such as routing, coordination, and coverage, yet the integration of sophisticated mechanisms for payload interaction remains underdeveloped.

Deep learning has revolutionized multiple domains, particularly in fields like computer vision and natural language processing, where convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have set new benchmarks in performance. In robotics, these architectures have been pivotal in advancing perception tasks, including object recognition, scene understanding, and even autonomous navigation. Despite these advancements, applying deep learning to the specific challenge of payload manipulation within multi-drone systems is still in its early stages. The inherent complexity of dynamic payload manipulation, especially when multiple drones are involved, poses unique challenges that traditional deep-learning models are only beginning to address.

Reinforcement learning (RL) offers a promising avenue for overcoming these challenges, as it allows agents to learn optimal behaviors through interaction with their environment. In the context of multi-drone systems, multi-agent reinforcement learning (MARL) extends this capability by enabling multiple agents to learn cooperatively. This collaborative learning framework is crucial for tasks that require a high degree of coordination, such as the joint manipulation of an unknown or shifting payload. While MARL has shown potential in various cooperative robotic tasks, its application to dynamic payload manipulation scenarios is still largely unexplored. The ability of MARL to adapt to the real-time demands of payload manipulation, where conditions and requirements can change rapidly, makes it an exciting area for future research.

Emerging research is beginning to address these gaps, exploring how deep learning and MARL can be leveraged together to enable more intelligent and adaptive multi-drone systems. By integrating advanced perception capabilities with learning-based control strategies, these systems could potentially handle the complexities of dynamic payloads in a way that traditional methods cannot. As research in this area progresses, we can anticipate significant advancements in deploying multi-drone systems for complex, real-world tasks, pushing the boundaries of what is currently achievable in aerial robotics.

9.3.3. Methodology

In this approach, each drone within the fleet is systematically registered onto a blockchain network, ensuring that all essential information is securely stored and easily accessible. The metadata associated with each drone includes a unique identifier detailing its specific operational capabilities, such as payload capacity, battery life, sensor accuracy, and current operational state. To maintain the integrity of this data, a deep learning-based classification algorithm is employed to verify and validate the reported capabilities of each drone. This algorithm analyzes the drone's performance metrics and cross-references them with the metadata to confirm accuracy, thereby ensuring that the information recorded on the blockchain is both precise and reliable.

This verification process, illustrated in Fig. 2, is a critical step in the workflow as it underpins the trustworthiness of the entire system. By ensuring that only validated data is stored on the blockchain, the system can confidently proceed with mission planning and execution, knowing that decisions are based on accurate, up-to-date information. This layer of verification enhances the reliability of the individual drones and contributes to the overall robustness of the fleet's operations, which is vital for the success of complex missions.

To formalize the deep learning-based method used for multi-robot (multi-drone) transportation tasks, let's define the necessary components and the equations involved. The deep learning method, in this context, is focused on classifying and validating the capabilities of each drone in the fleet to ensure successful transportation tasks. Let each drone i in the fleet be represented by a feature vector $\mathbf{x}_i$ that encapsulates its operational capabilities:

$$\mathbf{x}_i = \begin{pmatrix} C_i \\ B_i \\ S_i \\ \mathbf{s}_i \end{pmatrix}$$

Where C_i represents the payload capacity of drone i, B_i represents the battery life of drone i, S_i represents the sensor accuracy of drone i, $\mathbf{S}_i$ represents the current state of drone i, which may include parameters like position, velocity, and operational status.

A deep neural network (DNN) $f(\mathbf{x}_i;\theta)$ is trained to classify the operational state and capabilities of the drones. The function f maps the input feature vector $\mathbf{x}_i$ to a classification output $\hat{y}_i$, which represents the validated capability status:

$$\hat{y}_i = f(\mathbf{x}_i;\theta)$$

Where θ represents the parameters of the neural network, $\hat{y}_i$ is the predicted class label for drone iii, indicating whether the capabilities are valid (1) or not valid (0).

The deep learning model is trained using a loss function $\mathcal{L}$ that measures the difference between the predicted label $\hat{y}_i$ and the true label y_i (ground truth):

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell(y_i, \hat{y}_i)$$

Where N is the number of drones in the training set, $\ell(y_i, \hat{y}_i)$ is the loss function (e.g., cross-entropy loss) for a single drone i.

Once the model is trained, it is used to validate the capabilities of each drone before the information is recorded on the blockchain. The final validation for drone iii can be expressed as:

$$\text{Validation Status } = \begin{cases} \text{Record on Blockchain} & \text{if } \hat{y}_i = 1 \\ \text{Reject} & \text{if } \hat{y}_i = 0 \end{cases}$$

This equation dictates that only drones classified with valid capabilities $(\hat{y}_i = 1)$ will have their data recorded on the blockchain, ensuring the accuracy and reliability of the operational data.

The feature vector $\mathbf{x}_i$ represents each drone's operational capabilities and current state, which are essential for the transportation task. The deep neural network $f(\mathbf{x}_i;\theta)$ is used to classify whether these capabilities are valid based on the training it received with a labeled dataset. The loss function $\mathcal{L}(\theta)$ helps optimize the network during training by minimizing classification errors.

Once trained, this deep learning model becomes an integral part of the verification process, ensuring that only drones with validated and reliable capabilities store their data on the blockchain. This process safeguards the integrity of the entire multi-robot transportation system, ensuring that all mission-critical operations are based on accurate and trustworthy data.

Once the drones are registered, the system transitions to task allocation. Here, a reinforcement learning (RL) framework [381] is leveraged to assign specific roles to each drone, such as gripping, stabilizing, or monitoring. The RL model is trained to maximize efficiency by considering factors like drone capabilities, current energy levels, and the object's characteristics [382]. The RL algorithm iteratively refines task assignments to minimize energy consumption and ensure balanced workload distribution among drones [383]. The algorithm design is done by enhancing overall mission efficiency. Our algorithm design is shown in Fig.3.

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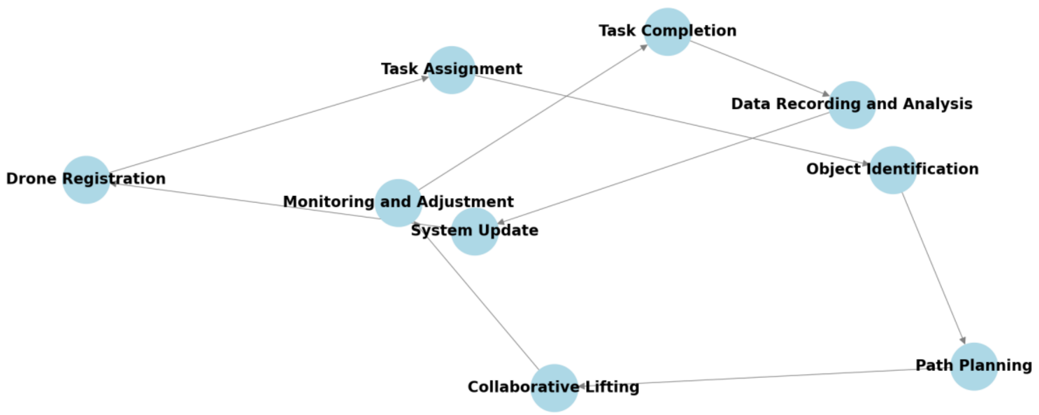

Figure 2. Algorithm design for Deep Learning in multi-drone lifting task.

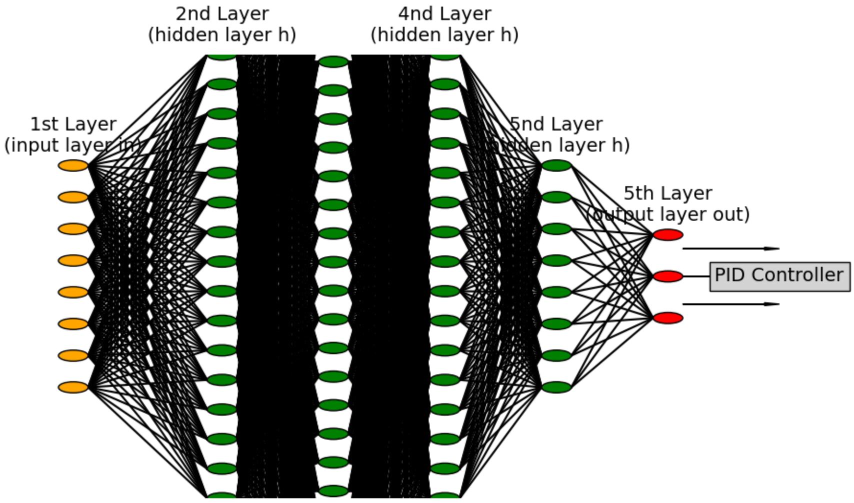

Figure 3. Deep Neural network structure in low-level control.

9.3.4 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.

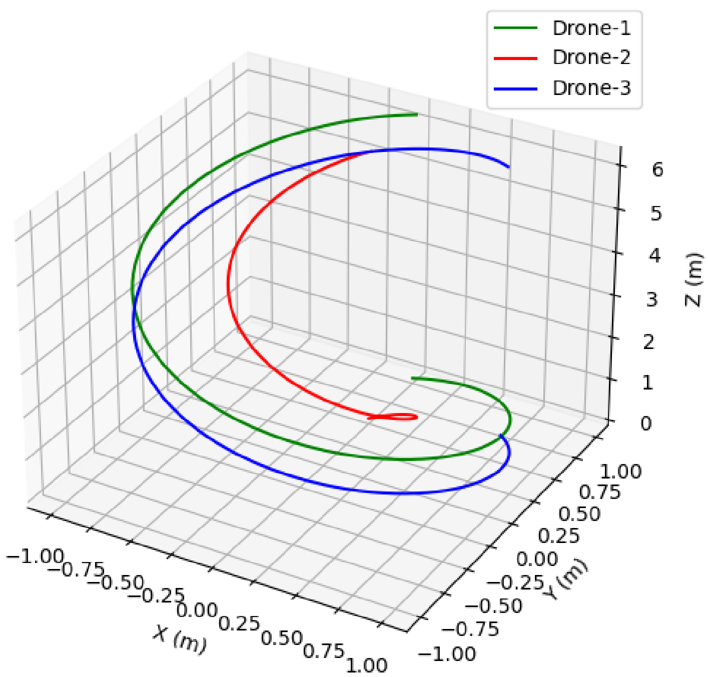

Figure 4. Trajectory tracking results for three drones during our transportation task.

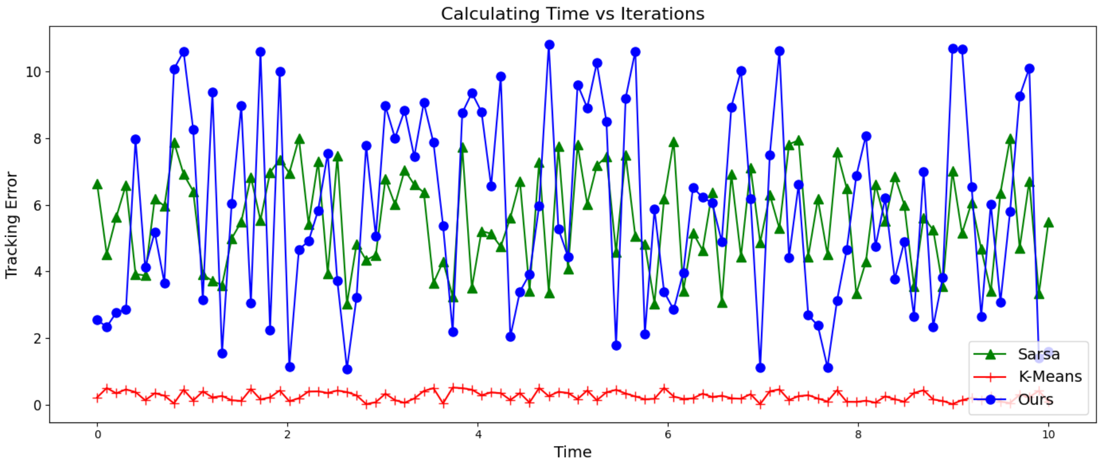

Figure 5. Tracking errors with other two popular methods during the same task.

9.3.5 Conclusion

This paper presents a novel multi-drone system capable of manipulating unknown payloads by leveraging deep learning and reinforcement learning techniques. Our findings indicate significant potential for various applications that require autonomous payload manipulation, underscoring the need for further research and development in this domain.