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# Challenges in Multi-domain Robot Swarm for Industrial Mapping and Asset Monitoring

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**Abstract**

Heterogeneous systems integrating ground-mobile vehicle robots and drone UAVs to perform indoor mapping and explore complex operational environments such as industrial areas where the obstacles take places. Despite their potential to enable advanced autonomous exploration with self-reinforcement learning and navigation capabilities, these systems face multiple challenges related to communication, coordination, security, and landscape mapping. This paper discusses the challenges associated with implementing heterogeneous robot systems and examines relevant research articles that contribute to addressing them. Firstly, determining the most effective localization method in unstructured environments, where traditional navigation aids might be limited, poses a significant hurdle. Vision-based approaches for landing the drones on a mobile robot introduce complexities that require innovative solutions. We also need to address the communication challenges that demand real-time and secure data exchanges between vehicular and drone robot systems. Moreover, the limitations of GPS in indoor environments necessitate alternative positioning solutions. Additionally, coordinating leader-follower dynamics between drones and mobile robots requires sophisticated strategies to ensure smooth collaboration and effective mapping. This paper comprehensively examines these challenges and explores relevant research articles that contribute to addressing them, shedding light on potential solutions and avenues for future research.



*Keywords:* **Robot-to-robot communication; Heterogeneous robot systems; Autonomous exploration; SLAM technology; Real-time communication; Secure data exchange.**

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## 1. Introduction

In recent years, robot-to-robot communication has gained popularity and significant attention in various domains, ranging from industrial automation to surveillance to environmental monitoring Bouachir et al. [2020]Lee et al. [2021] Mahdoui et al. [2020]. One of such applications is the use of vehicular robots with unmanned aerial vehicles (UAVs) or drones for mapping the floor plan and to perform exploration tasks in an indoor complex environment. With the advent of drone technologies and artificial intelligence based deep learning technique for object detection, multi-robotic based heterogeneous systems can be used to explore complex environment such as industrial plant where traditional mapping techniques often rely on manual surveys Lashkari et al. [2018]. The main motivation in developing an heterogeneous system consisting of both ground-based vehicular robot and aerial drone lies in leveraging the complementary strengths of each platform to overcome the inherent limitations of individual systems. It is known that indoor environments present unique challenges for robots due to complex layouts, obstacles, and dynamic elements Javaid et al. [2024]. Traditional mobile robots rely on ground-level sensors (e.g. LiDAR) for navigation and mapping while traversing indoor areas. The complex environment can limit their capabilities to capture a complete picture of the complex industrial settings. Whereas, aerial drones provide a unique aerial or 3D perspective, enabling detection of obstacles from above. Therefore, an heterogeneous robot systems, combining ground vehicular robots and aerial drones, offer significant advantages in capturing overall environment features. By combining these capabilities, the heterogeneous system aims to enhance the efficiency and accuracy of mapping tasks, particularly in scenarios where a comprehensive understanding of the environment is crucial. Such hybrid systems face multiple challenges associated with implementing a heterogeneous system comprising a ground vehicular robot and a drone for cooperative mapping of an indoor area Javaid et al. [2024]Javaid et al. [2023]. In this paper, we focus on addressing the challenges associated with the implementation of above mentioned heterogeneous systems that can help in mapping of indoor complex environment. Figure 1 was taken while the research team was investigating the challenges.

One of the primary challenges is detailed in section 2 that discusses challenges related to utilizing of computer vision for autonomous landing of UAV. Section 3, is related to building an AI model that would be deployed on drones to extract digital meter readings from sensors deployed in high-rise and difficult-to-reach places. Section 4 discusses challenges of implementing 2D SLAM for ground robot, especially in complex industrial environments. Lastly, section 5 discusses challenges related to protocol selection for real-time and secure communication between ground robot and drone.

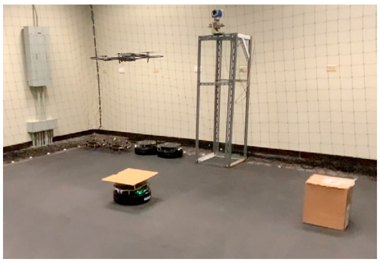

Fig. 1: Experimental Setup for Drone to Vehicular Robot communication.

## 2. Technical Challenges of Using Computer Vision for Autonomous Landing

As well known, the GPS has been used for navigation to provide an accurate landings for a long time, however it has some limitation such as accuracy, signal dependency, and adaptability problems. The recent techniques such as Differential GPS (DGPS) and Real-Time Kinematic (RTK) provide great precision but still have restrictions for instance require additional equipment and relying on base stations, which may make them expensive and unworkable under some situations. Alternatively, computer vision technology shows promise in providing improved accuracy and flexibility in changing conditions. Nevertheless, several technical challenges remain in this field which need to be addressed and solved.

The rapid progress in the computer vision technology indicates an important shift in navigation systems and provides a compelling alternative which is more precise and adaptive, specifically in surroundings with changing conditions. However, this new technology has its own complexities and some associated challenges such as algorithmic resilience, computational efficiency, and environmental variability. The optimization of computer vision techniques for smooth integration into UAV navigation systems remains a major challenge, even in the presence of the recent advancements.

### 2.1. Real-Time Processing Requirements

Computer vision models help in deriving valuable information from visual data, in terms of images, videos, or both, but their computational needs must be carefully considered. This becomes particularly crucial when dealing with limited resources and when processing images and videos in real-time. Although a little simplified, the claim that establishing a necessary balance between inference speed and data correctness is critical is true. Strong processing power is in fact required for the deployment of complex algorithms and high-resolution images, especially deep learning models. But this necessity is a difficult task, particularly when compared to the limits that come with UAVs, such as weight and size restrictions. An issue that requires careful investigation is created by the natural trade-off between processing power and the physical limitations of UAVs. The optimization of algorithms for resource-constrained contexts is still a work in progress, despite great advancements in computational efficiency, which emphasizes the need for more comprehensive solutions that go beyond traditional paradigms Schneider et al. [2019].

### 2.2. Lighting and Environmental Conditions

As UAVs depend more and more on video cameras for accurate landings and navigation, it is critical to make sure these cameras work well in a variety of illumination scenarios. But still, low light conditions for example often cause conventional cameras to frequently malfunction, producing footage with poor quality that jeopardizes the security and effectiveness of autonomous operations. While infrared cameras can improve visibility in these kinds of situations, their usefulness depends on the existence of temperature differences between the objects and their environment. This limitation makes infrared cameras useless when important landing zones, like assigned pads or areas, don't have any noticeable temperature differences. Furthermore, a variety of lighting situations, such as glare, shadows, and low light levels, can affect how well computer vision systems function. Environmental factors that obscure the camera's field of view, such as fog, rain, or dust, make these difficulties even more difficult to navigate and compromise operational integrity Hussain et al. [2020].

### 2.3. Object Detection and Identification for Landing Scenarios

Navigating UAVs in complex scenarios is a challenging task. One of the biggest challenges that UAVs face is to locate and identify the landing platform. This becomes more problematic, particularly in congested or complicated surroundings. To distinguish the landing target from other elements and objects in the environment, the UAV needs to be equipped with robust object identification and classification models Redmon and Farhadi [2018].

### 2.4. Pose Estimation Accuracy

To land a UAV without any error, an accurate estimation of its position relative to the landing platform is critical. In cases of errors, their presence in pose estimation can lead to misalignment and unsuccessful landing attempts. To achieve high accuracy in pose estimation, the solution requires precise calibration and robust algorithms Liu et al. [2020].

Furthermore, during daylight, the varying angles and movements of the UAV in relation to the sun lead to fluctuations in the amount and direction of light hitting the camera sensor. This dynamic lighting environment can make it difficult for the camera to capture clear and accurate images of the landing target. This presents a challenge for systems relying on image recognition for tasks like autonomous landing, where precise identification of landing targets is crucial for safe and successful operations Baca et al. [2019].

(a) Meter Image (b) Mask for Training (c) Output for Region of Interest

Fig. 2: Sample for Illustrating the extraction of Region of interest

### 2.5. *Latency and Communication Delays*

The latency in processing visual data and the communication delays between the UAV and the ground control system can affect the responsiveness of the landing system. This is critical when dealing with fast-moving platforms, where timely decision-making is essential Schneider et al. [2019]. Mitigation Strategies: Reducing algorithmic complexity, improving communication protocols, and employing edge computing to process data locally on the UAV can reduce latency and improve responsiveness.

## 3. Challenges of Developing AI Model for Extracting Digital Meter Readings

As robot and drone move in an environment, they need to identify point-of-interest autonomously. In this work, we set the point-of-interest as the digital numbers that appears on a meter reading, see Fig. 2a. In this section, we present the challenges faced in developing AI model that can extract digital numbers from meter readings.

### 3.1. *Mask Region of interest*

The image processed by a camera contains both digital meter reading and background. So, first we need to mask the area where the digital numbers exist. So, we build an AI model that mask the region of interest. To do this, we utilize the U-Net Segmentation model architecture and fine-tune it with our custom dataset. In the training phase, we input the original image along with its masked image. Once the model is trained, we input the original image to predict the masks for unseen images. Fig. 2a shows an example of an original image. Fig. 2b shows an example of a mask that is inputted to the model in training phase. Fig. 2c shows the output of the trained model after training with only the original image as an input to the model. The dataset utilized in this work is available online on Kaggle [1].

### 3.2. *Optical Character Recognition (OCR) for Accurate Digit Extraction*

OCR is a system that converts the input text into machine encoded format Tappert et al. [1990]. Researchers have developed and optimized several tools for OCR. More recently, researches applied Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) for OCR performance improvement Srivastava et al. [2022]. According to analysis performed by Beerten Beerten [2023] on different techniques of OCR, Tesseract OCR and Paddle OCR performed better in digits extraction than other OCR techniques. Moreover, Paddle OCR support more than 80+ languages Du et al. [2020].

### 3.3. *Deploying AI Model for Real-time Image Processing from Drone*

Deploying AI models for real-time image processing from drones presents several unique challenges. The primary challenge is the need for high computational power and low latency, especially when processing high-resolution

[1] Dataset available at https://www.kaggle.com/datasets/tapakah68/yandextoloka-water-meters-dataset.

images or video streams in real-time. Another challenge is the variability in environmental conditions such as light Yeom [2024]. Despite these challenges, recent advancements in AI and drone technology have made it possible to deploy sophisticated AI models on drones. For example, the use of edge computing allows for real-time processing on the drone itself, reducing the need for data transmission and thereby saving bandwidth3.

## 4. Challenges of Implementing 2D SLAM for Ground Robot

Simultaneous Localization and Mapping (SLAM) is a pivotal technology in autonomous ground mobile robots, enabling them to understand and navigate complex environments with remarkable precision Nguyen et al. [2010]. This technology integrates the processes of creating a map of an unknown environment while simultaneously tracking the robot's location within that map. The efficacy of SLAM is not just about creating a map, where it can be extended to enhance the robot's ability to navigate autonomously and significantly boosting its adaptability to dynamic changes in its surroundings. As ground mobile robots continue to permeate various sectors, from industrial automation to urban transportation, where the SLAM technology is crucial in advancing their autonomy, reliability, and overall effectiveness in performing different tasks autonomously Duan et al. [2019], Liu et al. [2021], this adaptability and autonomy that makes SLAM technology a game-changer in the field of robotics.

### *4.1. Hardware Integration*

Integrating diverse sensor technologies and innovative methodologies has significantly enhanced the SLAM-based mapping processes, leading to more accurate and efficient solutions. Chen et al. [2018] analyzed various SLAM-based indoor mapping technologies, highlighting the importance of sensor setups such as LiDAR and depth cameras in achieving high mapping accuracies in complex indoor settings like corridors and libraries. The work in Sobczak et al. [2021] investigated hardware configurations with the Google Cartographer SLAM algorithm to determine optimal setups for tasks such as decontamination, advocating a multi-sensor approach using LiDARs, IMUs, and odometry for enhanced accuracy in simulations. Where, Duan [2023] proposed a multi-sensor fusion SLAM technique for smart factories, improving robustness and map accuracy by combining LiDAR and depth camera data. However, Wang et al. [2022] introduced a method that merges depth camera and LiDAR data, improving the mapping of sterile environments with the gmapping algorithm for better point cloud integration. Zheng et al. [2023] discussed a multi-sensor SLAM approach for autonomous driving, using LiDAR and GNSS/INS systems for precise mapping essential for navigation. Norzam et al. [2019] explored how different parameters such as robot speed, mapping delay, and particle filter affect the Gmapping-based SLAM technique, identifying settings significantly impacting mapping accuracy and processing speed.

However, rapid recent advancements in SLAM technology have significantly enhanced its application across various indoor and industrial settings. Studies have shown that the choice of sensors and their configuration plays a critical role in the accuracy and efficiency of SLAM-based mapping systems. Furthermore, the fusion of data from multiple sensors can substantially improve the quality and robustness of the resulting maps. Future research should continue to explore these areas, particularly integrating new sensor technologies and optimizing SLAM algorithms for specific applications.

### *4.2. Software Compatibility*

The development of Robot Operating System 2 (ROS2) has been a significant breakthrough in mapping and navigation Gyanani et al. [2024]. ROS2 is designed for building robotic applications and provides tools, libraries, and communication infrastructure. ROS includes application tools like Rviz, which visualizes the created map, and Gazebo, which allows testing in a simulated environment Jha et al. [2024]. Two major algorithms are commonly used in mapping with ROS: The first algorithm called Cartographer, developed by Google, is more accurate but computationally demanding, requiring a powerful computer. While the second algorithm is SLAM which provides reasonably accurate mapping, and its a fundamental technique for building maps while estimating the robot's position. Still, it is less computationally intensive, making it a viable option for implementation on processors used in robotics, such as the Raspberry Pi.

Andreasen et al. [2023] presented performance tests, where its conducted with rather modest hardware, showing that Multi-Agent Exploration Simulator (MAES) is able to simulate up to 5 robots in ROSMode (using the ROS integration) and up to 120 robots in UnityMode. The proposed architecture presented in Bianchi et al. [2023] is for quadcopter UAV was based on the ROS2 middleware, offering distributed control, scalability, soft real-time communication, security features, optimized implementations of localization algorithms, and a flexible path planner.

The study in Roldán et al. [2019] described in details the integration for ROS-based robots with Unity-based virtual reality interfaces, where the main objective from this integration is to develop immersive monitoring and commanding interfaces, and this objective was achieved by analyzing the available technologies, resources and multiple ROS packages where the Unity assets are implemented, for instance *multimaster_fkie*, *rosbridge_suite*, RosBridgeLib and SteamVR. Three scenarios of applications are performed: an interface for monitoring a fleet of drones, another interface for commanding a robot manipulator and an integration of multiple ground and aerial robots.

## 5. Real-Time and Secure Communication Protocol Selection for Ground Robot-Drone Interaction

Technological solutions utilizing both drones and ground robots are gaining popularity in different industrial and commercial sectors Mohsan et al. [2023]. Therefore, achieving seamless communication between ground robots and drones is crucial for various mission-critical applications, from industrial automation to surveillance Abir et al. [2023]. However, this integration poses significant challenges in terms of real-time communication, secure data exchanges, and open-source cross-platform communication framework Chai et al. [2024].

### *5.1. Real-time Communication and Latency Management*

UAVs and robotic vehicles need real-time communication to exchange messages for the purpose of coordination and expedited decision-making. Nevertheless, variations in network conditions and processing delays may cause latency, which might impact the system's ability to respond promptly Kurunathan et al. [2023]. When it comes to autonomous landing, even small delays in delivering positioning data or control signals might result in misalignment or crashes. To tackle latency, it is necessary to optimize communication protocols, provide priority to vital data packets, secure data exchanges and use edge computing technologies to reduce processing time.

### *5.2. Secure Data Exchange*

The challenge lies in selecting the most suitable communication protocol to ensure secure data sharing between these heterogeneous systems. Secure communication is a concern in real-time communication, as security breaches can have immediate and long-term consequences. DDS supports various security mechanisms, including data encryption and authentication, to ensure secure data sharing between the mobile robot and the drone Lee et al. [2021].

### *5.3. Open source Cross-platform Communication Framework*

In addition, the other related issue is the compatibility between the operating systems of the ground mobile robot and the drone Pillai et al. [2024]. To build an open-source system capable of facilitating effective communication between ground robots and drones, it is necessary to address the compatibility concerns stemming from the diverse operating systems in use. The need for cross-platform and secure communication protocols that can bridge this gap is essential. The communication also needs to be in real-time to avoid moving obstacles for both ground robots and drone systems Kalidas et al. [2023].

### *5.4. Interference and Signal Degradation*

In the case of communication between drones and mobile ground robots, the quality of the communication signals may be affected by many environmental sources such as electromagnetic and radio frequency interference in addition to physical obstacles Mohsan et al. [2023]. If this happens, the communication reliability will be reduced. On the other hand, the time for receiving data will be increased.

### 5.5. Bandwidth Constraints

The bandwidth has constraints, especially when transmitting large volumes of data in real time and this harms communication efficiency Lu et al. [2024]. As a result, some optimization techniques can be used to overcome this limitation in addition to using multi-channel communication.

## 6. Conclusion

In this paper, numerous challenges were discussed which could be faced in successful development of heterogeneous system consists of vehicular robots and UAV. It was found that traditional navigation methods will fall short for such systems. Similarly landing UAV on floor or flat surface needs innovative vision-based solutions. Similarly, implementing 2D SLAM for ground robots presents technical obstacles that must be overcome to ensure accurate mapping and navigation. Lastly, Real-time and secure communication between ground robots and drones is essential for seamless collaboration and effective data exchange, adding another layer of complexity to system integration. For the future work, our aim is to develop solutions that can tackle these challenges holistically.

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