Advanced Robotics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tadr20

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To cite this article: Branesh M. Pillai, Jackrit Suthakorn, Dileep Sivaraman, Sakol Nakdhamabhorn, Nantida Nillahoot, Songpol Ongwattanakul, Fumitoshi Matsuno, Mikhail Svinin & Evgeni Magid (06 Feb 2024): A heterogeneous robots collaboration for safety, security, and rescue robotics: e-ASIA joint research program for disaster risk and reduction management, Advanced Robotics, DOI: 10.1080/01691864.2024.2309622

To link to this article: https://doi.org/10.1080/01691864.2024.2309622

Published online: 06 Feb 2024.

ADVANCED ROBOTICS
https://doi.org/10.1080/01691864.2024.2309622

FULL PAPER

A heterogeneous robots collaboration for safety, security, and rescue robotics: e-ASIA joint research program for disaster risk and reduction management

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ABSTRACT
In the face of humanitarian crises such as torrential rainfall, resulting floods, and landslides, rapid rescue operations are often imperative. However, owing to the inherent dangers and unpredictability of such circumstances, immediate on-site aid delivery is frequently unfeasible. In such challenging scenarios, mobile robot systems have emerged as the optimal solution for aiding search and rescue efforts. The 'Informational system for management of flood and landslide disaster areas using a distributed heterogeneous robotic team' project, initiated by the International e-ASIA Joint Research Program, united research teams from Japan, Russia, and Thailand, each contributing unique expertize and experience towards common objectives. Drawing upon our extensive theoretical and practical knowledge in disaster response research, we developed an integrated international operational framework for disaster site management, centered on dispersed, heterogeneous semi-autonomous Unmanned Aerial Vehicles (UAVs), Semi-Autonomous Rough Terrain Vehicles (UGVs), and Semi-Autonomous Surface Vehicles (USVs). This paper provides an overview of the methodologies, models, and algorithms employed throughout the successful three-year project conducted by the Thailand team while also directing interested readers to supplementary research papers for in-depth insights.

ARTICLE HISTORY
Received 29 April 2023
Revised 5 November 2023
Accepted 24 December 2023

KEYWORDS
Rescue robotics; search and rescue; heterogeneous multi-robot systems; informational system; path planning algorithms

1. Introduction

Worldwide, there is an urgent need for intelligent robots for disaster response, with implications spanning robotics research, industry, and emergency services [1–4]. These robots are essential because of their ability to operate effectively in hazardous environments such as collapsed structures, toxic atmospheres, and radioactive areas, where human rescuers may struggle to provide immediate aid [4–6]. Numerous organizations and research groups are actively developing rescue robots to support Safety, Security, and Rescue Robotics (SSRR) teams [7–11]. These mobile robots are equipped with a wide array of sensors, actuators, and embedded processing units tailored to their specific operational environments [12]. Their construction grants them the agility needed for their designated terrains, enabling them to conduct mapping, search and rescue, and reconnaissance tasks by processing the data collected through their sensors. They can operate autonomously or semi-autonomously, which proves invaluable in situations such as collapsed structures where remote control may not be feasible. These robots must be capable of autonomous localization and navigation in unfamiliar environments, while also managing their power resources. Even when an area map is available, its accuracy may deteriorate, particularly in the wake of natural disasters. Thus, robots often require the autonomous localization and reconstruction of environment maps without human intervention [13]. Furthermore, in multi-robot scenarios, it is imperative for robots to identify locations and engage in effective communication, particularly for tasks requiring instant collaboration [14,15]. Effective path-planning algorithms are crucial for determining the optimal route to a specific target, considering the generated map and current robot locations. Consequently, to enhance task efficiency, multiple robots must collaborate and integrate optimal energy-consumption models and algorithms.

As part of the e-ASIA Joint Research Program, an international operational framework for disaster site management involving distributed heterogeneous

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robotic teams was collaboratively developed by teams from Japan, including Kyoto University and Ritsumeikan University; Russia, represented by Kazan Federal University; and Thailand's Center for Biomedical and Robotics Technology (BART LAB) within the Faculty of Engineering at Mahidol University [1,16]. The project, funded by three national governments, focused on the integration of interaction protocols and thematic mapping within an information-collecting system tailored for emergency situation management. This initiative provides not only a comprehensive framework but also a collection of algorithms and control methods that foster collaborative learning among both homogeneous and heterogeneous robotic teams. The three national teams utilize different sets of robots, each equipped with distinct sensors and protocols, to maximize sensory input and simulate diverse real-world disaster scenarios, including torrential rain, floods, landslides, and earthquakes. Specifically, the Thailand research team is developing Semi-Autonomous Unmanned Aerial Vehicle (UAV), Semi-Autonomous Rough Terrain Vehicle (UGV), and Semi-Autonomous Surface Vehicle (USV) for flood management and landslide defense, which can operate in teleoperated or semi-autonomous modes. Real-time data from these robots were continuously transmitted to a central control station for monitoring and coordination.

The Thailand research team strategically concentrates its efforts on building heterogeneous robotic systems and the integration and optimization of robotic sensor systems and advanced communication tools within the realm of Safety, Security, and Rescue Robotics (SSRR). These technologies, including sensors, communication protocols, graphical user interfaces (GUIs), object detection, diameter (volume) estimation, analysis of objects/targets (object of interest (OOI)) in SSRR environments, and 3D reconstruction of rescue areas (region of interest (ROI)), play a pivotal role in enhancing the effectiveness of rescue operations. These technologies enable robots to collect real-time data, identify potential hazards, and locate victims accurately. In addition, these advancements facilitate optimization of the path planning and decision-making processes for multiple robots operating collaboratively in complex and dynamic SSRR scenarios. Furthermore, there is a problem that it's hard to use regular cooling methods for rescue robots in hazardous environments with water, and dust. To solve this problem, electronic boxes for rescue robots and the ability to cool these electronic components during missions are vital for sustaining a robot's performance and ensuring mission success. In summary, these integrated technologies empower robots to navigate, assess, and respond in high-stake scenarios, ultimately saving lives and reducing risks to human responders.

This study introduces a novel approach to heterogeneous robot collaboration, uniting a UAV, UGV, and USV to address real-world SSRR scenarios. Each robot has a specific role in locating and aiding humans or targets that are in need. The foundation of this collaborative localization problem is rooted in the aerial perspective provided by the UAV, as ground and water robots autonomously/semi-autonomously chart their courses to predefined targets based on the UAV guidance. The primary objective of this research is to establish a comprehensive end-to-end collaborative robot scenario while considering the inherent limitations of available robots. Unlike many theoretical studies, this work leverages widely accessible aerial, water, and ground robots, each endowed with distinctive implementation capabilities and constraints. Given the multifaceted nature of SSRR scenarios, this cooperative robotic endeavor has been developed as a proof-of-concept integration study and demonstrated through test executions to exemplify its practical utility. Its applicability and scientific contributions are at the forefront of research, offering a unique perspective. By putting this heterogeneous-robot approach into action, we explore an extensive array of problem-solving possibilities, considering variations in surroundings, sensors, and specifications.

1.1. Project goals

The BART LAB (Thailand) team's project aims to develop a comprehensive framework governing the cooperative behavior of a heterogeneous robotic team, focusing on sensing, monitoring, and mapping flood and landslide disaster sites. This framework incorporates a wide range of technologies including novel electronic system protocols for rescue robots, advanced path planning, efficient battery management, innovative software solutions, and user-friendly control interfaces (Figure 1). The key to our approach was the deployment of heterogeneous UAV/UGV/USV robotic teams, each following the framework directives. Extensive real-time field testing, meeting the standards set by the National Institute of Standards and Technology (NIST), and in a controlled outdoor environment was conducted to validate the newly introduced control strategies, interfaces, and communication protocols. Further details and references for these technologies are provided in subsequent sections.

Following an elucidation of the outcomes resulting from this fruitful three-year endeavor, which encompasses the techniques, models, and algorithms developed by the Thailand team, we invite readers to delve into associated research articles for a deeper understanding of our work.

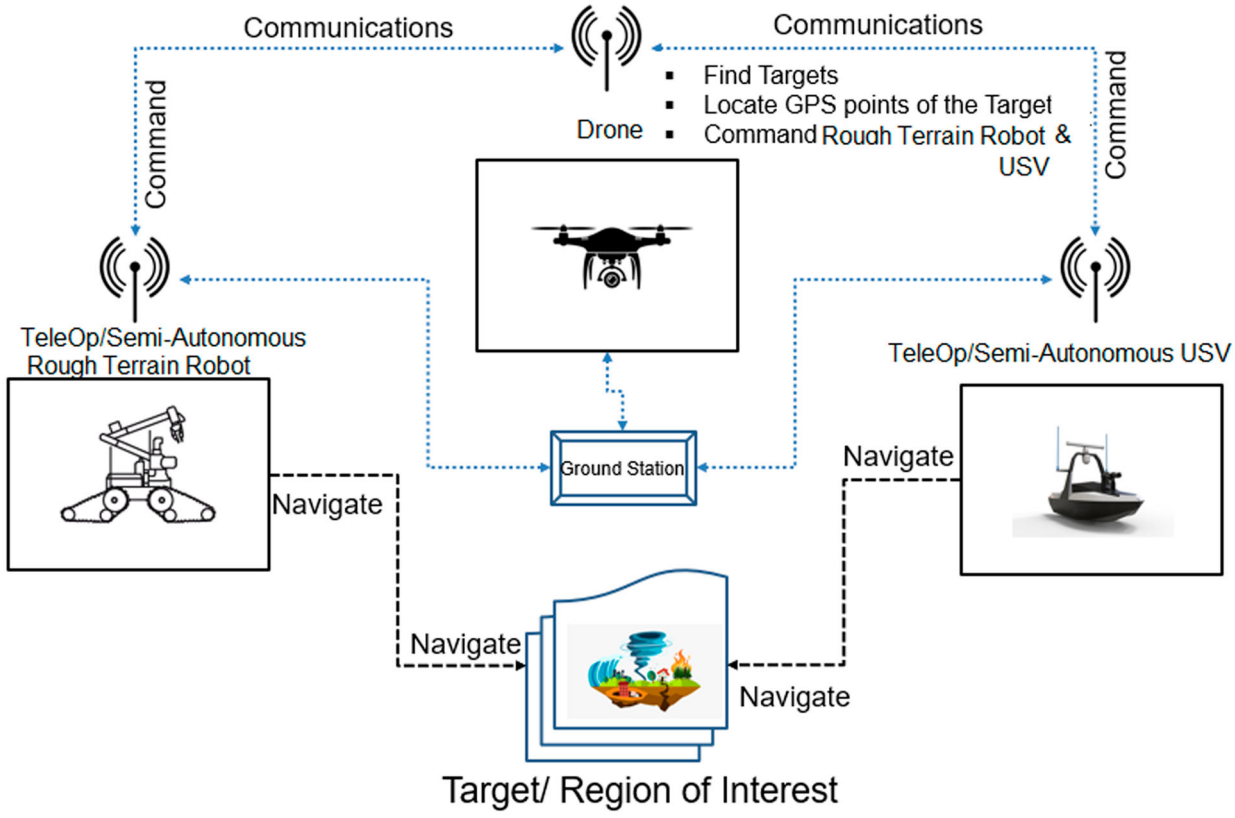


Figure 1. An overview of the project framework for heterogeneous robotics in landslide disasters.

The previous and related studies are presented in Section 2. Section 3 describes the project methods, including detailed information on the equipment and sensors that support the proposed collaboration model. In Section 4, the execution procedures of the proposed approach are described in detail, starting with aerial robot mapping operations and concluding with the ground-water robot localization of human victims/targets in an unknown environment. This section also describes the necessary proof-of-concept testing to demonstrate the full system in real-world trials in an outdoor setting. Section 5 concludes the paper with a brief discussion of the findings and the future perspectives of this study.

2. Related works

Queralta et al. [4] provided an extensive review of search and rescue operations, although it referenced only a few related studies. Notably, the European Union funded several crucial projects aimed at advancing human-robot collaboration in dynamic and challenging environments, particularly within search and rescue contexts.

The 'Natural Human-robot Cooperation in Dynamic Environments (NIFTI)' project, running from 2010 to 2013, was a pioneering initiative that sought to enhance cooperation between humans and robots in rapidly changing conditions, including search and rescue operations. It addresses a diverse range of topics from enabling robots to adapt to shifting environmental conditions to advanced sensory data processing and autonomous navigation in demanding surroundings [17–20].

Running from 2012 to 2015, the 'Deployable SAR Integrated Chain with Unmanned Systems (DARIUS)' project, also funded by the European Union, focused on addressing the technological and administrative challenges associated with the use of Unmanned Aerial Vehicles (UAVs) in search and rescue operations [21].

The 'ICARUS' project, funded by the European Union and spanning from 2012 to 2016, centered on heterogeneous robotic groups and their potential for cooperation to enhance the effectiveness of search and rescue robotics at disaster sites [22,23].

From 2013 to 2017, the 'TRADR' project, also funded by the European Union, explored novel approaches to environmental representation, data collection, and analysis. This project concentrated on sensory data processing and its application in navigation while also addressing challenges related to crawler robot models and human-robot interfaces [24–27].

Additionally, the European union-funded 'SHERPA' project (2013–2017) was motivated by the concept of

using robots to search for victims in mountainous terrains [28]. In the early years, the project relied on WiMAX technology [29] for agent communication, but it gradually lost importance because of the dominance of the LTE family of technologies [30]. The project introduced an innovative manipulator mechanism for UAVs [31].

In the IMPACT-TRC project (2014–2019), which received support from the Japanese government, more than 50 organizations, including Japanese universities, research institutions, and IT firms, collaborated with the shared goal of devising robust strategies for Search and Rescue Robotics (SARR) applicable in the most challenging scenarios, such as natural or man-made disasters [32]. This remarkable coalition of governmental bodies, research institutions, and corporations has unearthed a wealth of possibilities for robotics applications, ranging from outfitting search dogs with sensor-equipped protective gear [33] to the deployment of snake robots for rapid debris exploration [34].

In 2020, Chatziparaschis et al. developed collaborative aerial and ground robots for autonomous mapping in search-and-rescue missions [12]. Their innovative approach involved the synchronous collaboration of a UAV and a humanoid robot to address local search and rescue challenges, even without relying on conventional global positioning systems (GNSS). The humanoid robot utilizes a path-planning algorithm to estimate its goal location based on the information received from the UAV. Furthermore, the UAV determines the ground robot's position within the map frame by detecting an Augmented Reality (AR) marker affixed to the ground robot's head and by considering the ground robot's self-position information [12]. Nevertheless, it is worth noting the limitations associated with AR markers, especially when operating outdoors or during nighttime. Challenges may arise, such as light reflection interfering with marker detection. The effectiveness of the marker depends on the strong borders and high contrast between black and white colors [35,36].

Ni et al. [37] introduced a real-time path-planning solution for an unknown 3D environment within a hybrid UAV/UGV system that involves multiple UGVs and UAVs. Their approach leveraged the Dragonfly Algorithm (DA), combined with a bio-inspired neural network and grid method, to model the 3D environment as a neural topology map. An enhanced DA was then applied to create a novel 3D dynamic movement model for multiple robots, significantly improving the real-time path-planning efficiency and providing superior guidance for heterogeneous UAV/UGV systems.

While these projects have made substantial contributions to the field of search and rescue robotics, the e-Asia project introduces a unique dimension in the form of a heterogeneous multi-robot communication and collaboration system. The objectives and methodologies of this project are expounded upon in the subsequent sections.

3. Methods

This section outlines the systematic approach employed by the Thailand team to configure a heterogeneous robot ensemble and execute a comprehensive rescue operation scenario. The experiments focus on three essential areas to enhance disaster response and safety during floods and landslides: firstly, the heterogeneous robotic platform for multi-robot coordination; secondly, critical robotic system components, including Communication Systems, User Interfaces, Human/Target Detection, and Dimensional Analysis, for effective communication, control, and information gathering in disaster-stricken areas; and lastly, the development of optimization techniques for Unmanned Ground Vehicles, focusing on energy optimization and thermoelectric cooling. These measures aim to improve disaster response efficiency and safety in flood and landslide scenarios. The following protocol was followed:

⇒ ***Experimental Protocol and Methodology for the Rescue Operation/Task of the Thailand team***

- **Robot Configuration:** Assemble a team of heterogeneous robots, including a UAV, UGV, and USV. Ensure that each robot is equipped with the necessary sensors and communication capabilities.
- **Scenario Setup:** Define a real-world SSRR scenario, simulating conditions (e.g. flooding (controlled outdoor environment), National Institute of Standards and Technology (NIST) Arena) or other emergency situations where human assistance is required.
- **Role Assignment:** Assign specific roles to each robot within the collaborative system. Designate the UAV as a coordinator for locating humans or targets that require assistance.
- **Communication:** Establish a robust communication network that enables real-time data exchange between robots and a central control station.
- **Navigation Planning:** Develop navigation algorithms and protocols for ground (UGV) and water (USV) robots to plan their paths independently based on information provided by the UAV. Ensure that robots can adapt to dynamic and challenging environments.
- **Initial Survey:** Beginning the experiment by initiating a simulated/outdoor environment/NIST Arena

disaster scenario. The UAV conducted an initial survey of the disaster area to identify potential targets and hazards.

- **Target Identification:** Using data from the UAV, the system identifies the locations of humans or targets in need of assistance. This information is relayed to the ground and water robots.
- **Path Planning:** The UGV and USV independently plan their paths to reach the identified targets. These paths must consider the unique capabilities and constraints of each robot.
- **Coordination:** The UAV serves as a coordinator, ensuring that the ground and water robots stay updated at target locations and dynamically adjust their paths as needed.
- **Rescue Operation:** The ground and water robots move to their designated targets using their sensors to navigate through the environment. They can operate in teleoperated, or semi-autonomous modes as required.
- **Real-time Monitoring:** Continuous monitoring progress of the robots and relay real-time data from their sensors to the central control station by using a GUI.
- **Performance Evaluation:** Assess the success of the rescue operation by considering factors such as response time, accuracy, and the robots' ability to adapt to changing conditions.

As detailed in the protocol, the deployment of heterogeneous robots occurred within the controlled environment of the NIST standard indoor arena and an outdoor scene scenario within the university campus (Mahidol University (MU), Thailand). The subsequent subsections provide a comprehensive account of robot collaboration methods, algorithms, and implementation particulars, starting from the initial mapping stage of the drone to the ground-water robot's collaborative path planning and target recognition. Figure 2 presents an illustrative representation of the methodology's control algorithm. Each subsection commences with an objective statement to facilitate the reader's comprehension of the overarching methodology.

3.1. BART LAB heterogeneous robotic platform

In this case study, we selected existing ground robotic platforms available at BART LAB and incorporated a newly constructed drone and a surface vehicle into our system. The utilization of different types of robots serves vital purposes in disaster response during events, such as floods and landslides. Each type of robot has unique capabilities for rescue operations, with UGV excelling in ground navigation, UAV providing an aerial perspective for locating targets or hazards, and USV performing well in water-related scenarios. This collaborative approach improves the speed and effectiveness of the disaster response, enhances rescue team safety, and increases the likelihood of saving lives during floods and landslides by addressing a broad spectrum of challenges in disaster scenarios. Detailed descriptions of the sensor, control, and mechanical design of robots are provided in the following subsections.

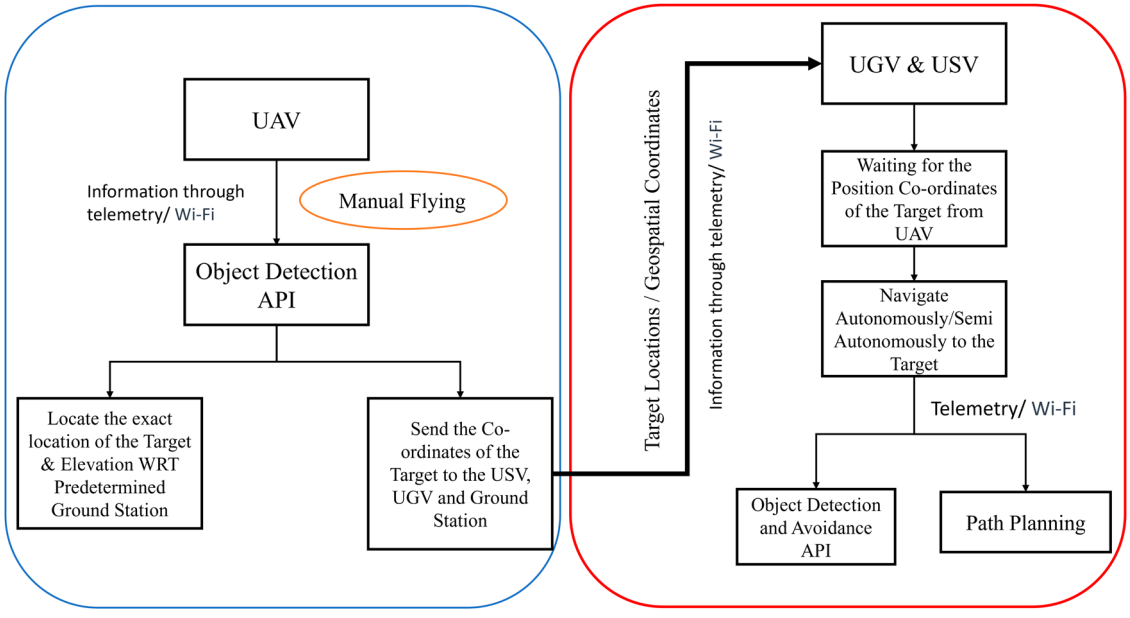


Figure 2. Methodological overview of the heterogeneous robots working flow of the operation.

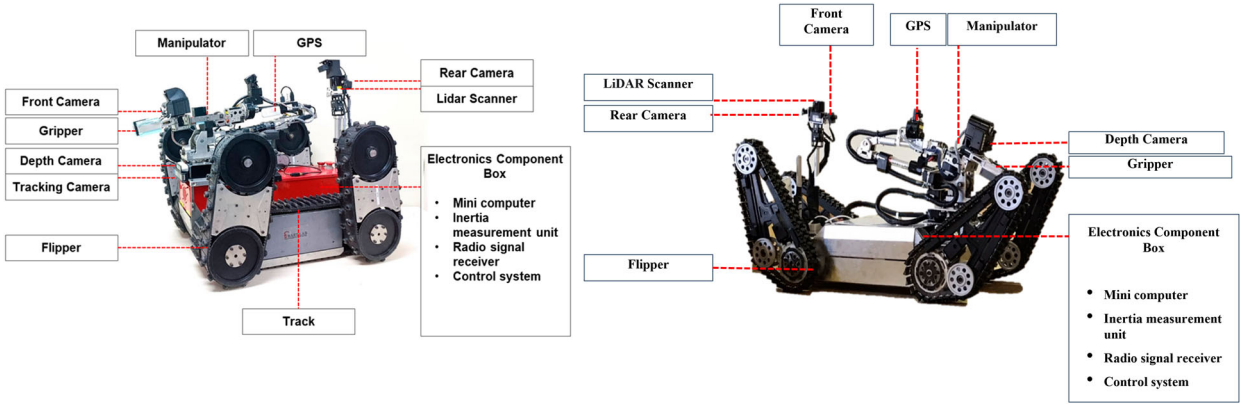


Figure 3. Semi-autonomous rough terrain vehicles – TeleOp VI and TeleOp VII.

3.1.1. Semi-autonomous rough terrain robot

The BART LAB TeleOp VI and VII robots, shown in Figure 3 [38], features a chassis equipped with four flippers: two at the front and two at the rear. These flippers are independently controlled to enhance maneuverability and stability while traversing diverse terrain. The robot also boasts an inverse kinematic-controlled manipulator with multiple degrees of freedom, utilizing both rotational and prismatic joints. This design allows the robot to be folded compactly while offering a versatile workspace. A manipulator was employed for precise end-effector movement and fine control. The primary purpose of TeleOp VI and VII is victim identification, facilitated by image processing and heat imaging technology. In addition to its manual control, TeleOp series leverages autonomous capabilities, utilizing laser-scanner technology and an efficient algorithm for self-navigation within testing environments and during rescue operations.

The victim-sensing unit, mounted on the end effector of the manipulator, plays a crucial role in identifying victims or targets and gathering essential information. This unit incorporates an array of vital signal detection sensors, including a camera, carbon dioxide sensor, heat sensor, LiDAR, and thermal sensor, all of which are used to search for vital signs. The robot was equipped with a two-way voice communication system. The sensors employed in this system are described in Table 1. The detection system for autonomous operation falls into two categories: (1) image detection, which employs a camera to monitor and analyze victim-related data, encompassing motion detection, QR code identification, and text reading from images, and (2) the thermal sensor, which is employed to detect the heat emanating from potential victims within the operational area. These thermal sensors were strategically positioned on the manipulator to identify any heat source that may indicate the presence of a victim.

Table 1. Robot components and specifications.

Robot	Components	Manufacturer and specifications
UGV	Depth Camera	Intel D435i
	LiDAR Sensor	Hokuyo UST-10LX – Lightweight 2D LiDAR – 270° field-of-view – Range: Up to 10 meters
	Thermal Camera	Adafruit MLX90640 IR Array
	Carbon Dioxide Sensor	MG811 Carbon Dioxide Sensor – CO2 Detection Gas Detector Module
	Thermal Sensor	OMRON D6T-32L-01A
UAV	Mini-computer	NVIDIA Jetson Nano Developer Kit Rev.B01
	Depth Camera	Intel D435i
	Flight Controller	Pixhawk PX4 Autopilot PIX 2.4.8
	FPV Camera	Foxeer Micro Cat 3 1200TVL – Super Low Light Night Camera
	Telemetry Radio	SiK Telemetry Radio V3
	FPV Receiver	RC832S – 5.8 GHz 48CH
	FPV Video Transmitter	PandaRC VT5801 V2/VT5805 – 5.8G 25–600 mW Switchable VTX
	Transmitter	SKYDROID T10 2.4 GHz 10CH FHSS Transmitter
	Receiver	R10/R10 Mini 10CH Receiver
USV	Mini-computer	NVIDIA Jetson TX2
	Depth Camera	Intel D435i
	LiDAR Scanner	SICK TIM781 LiDAR
	FPV Camera	Foxeer Micro Cat 3 1200TVL – Super Low Light Night Camera
	Telemetry Radio	SiK Telemetry Radio V3
	FPV Receiver	RC832S – 5.8 GHz 48CH
	FPV Video Transmitter	PandaRC VT5801 V2/VT5805 – 5.8G 25–600 mW Switchable VTX
	Transmitter	Flysky FS-i6X 2.4 GHz 10CH Transmitter
	Receiver	FS-iA6B Receiver FS-I6X

3.1.2. Semi-autonomous aerial robot

A Semi-Autonomous Unmanned Aerial Vehicle, commonly referred to as a drone, is constructed as a quadcopter with a 680 mm carbon fiber frame (ZD-680) designed for developers, as shown in Figure 4. The UAV's flight control system is based on the Pixhawk flight control system, which comprises two key components: a flight controller and an onboard mini-computer (Jetson Nano Developer Kit, NVIDIA Corporation, Santa Clara,

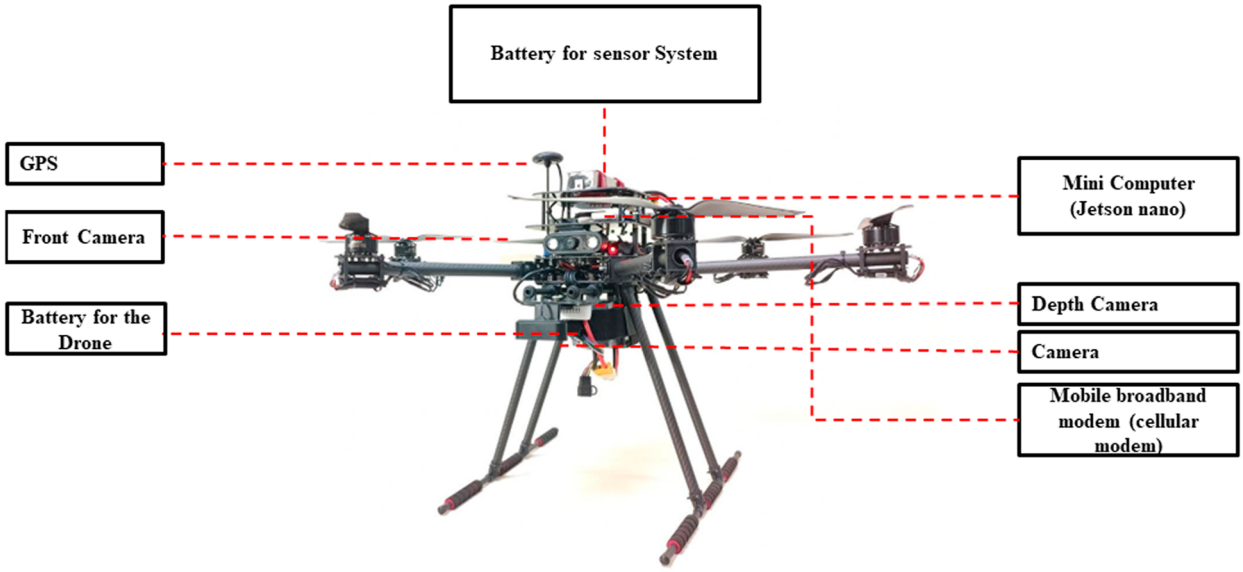


Figure 4. TeleOp/semi-autonomous aerial vehicle (BL-AIRBOT-II).

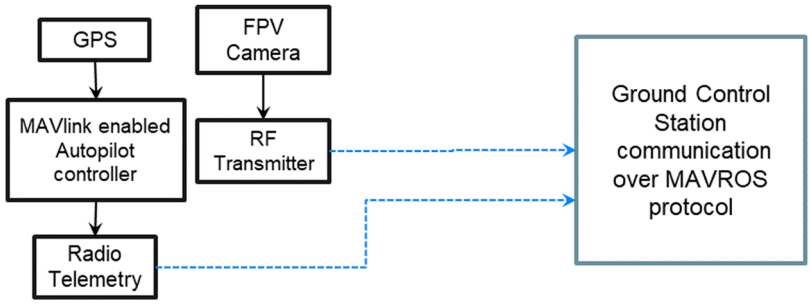


Figure 5. Communication using MAVROS.

California, U.S.). The flight controller is responsible for executing the drone's movements in response to control signals and interfaces with sensors, such as GPS. The drone's location is determined by extracting data from Pixhawk flight control using a Micro Aerial Vehicle Robotic Operating System (MAVROS). MAVROS incorporates the Micro Air Vehicle Link (MAVLink) communication library, which is an integral part of this comprehensive ROS package [39], and serves as a bridge for communication between ROS nodes and MAVLink-compatible flight controllers, as illustrated in Figure 5. Moreover, MAVROS offers a method for establishing a connection between a flight controller and a serial port.

In drone operations, two distinct radio frequencies are used for specific purposes. For First-Person-View (FPV) video transmission, we rely on the 5.8 GHz frequency. This frequency is the standard choice for real-time video transmission from drones to ground stations. This ensures a reliable and high-quality video feed for the operator during flight.

In contrast, we employed a lower frequency of 433 MHz for the GPS telemetry data transmission. This RF transmission is crucial for sending essential data, including GPS coordinates and other mission-critical information, from the drone to the ground station. The 433 MHz frequency offers excellent propagation characteristics, making it ideal for long-distance communication, even when the drone is operating at extended ranges (Table 1, featuring sensors and devices in Drone)

The primary processing unit for tasks such as object detection and 3D reconstruction employs an onboard computer. This computer is equipped with both an RGB camera and a depth camera (Intel® RealSense™ Depth Camera D435i, Santa Clara, California, U.S.)

3.1.3. Semi-autonomous surface vehicle

The Semi-Autonomous Surface Vehicle, as depicted in Figure 6, comprises key components, including the Pixhawk-controlled navigation system, RGB camera, and FlySky Remote and Receiver system (Shenzhen Flysky Technology Co., Ltd, China) for remote control. In a similar vein, the USV employed the same robust communication system to ensure efficient interaction with

the ground station. The vehicle's location is determined through data extraction from Pixhawk flight control using MAVROS. It is worth noting that the initial version of the developed USV exhibited certain limitations, including its compact size, limited stability, and restricted flexibility for the addition of additional components. The sensors employed in this USV are described in Table 1.

3.2. Robotic system components and functional elements

This section provides an extensive discussion of robots and sensors, commencing with an overview of collaborative and interactive approaches, as shown in Figure 7. The drone extracts depth information using a depth camera system for object and target identification. It employs a Robot Operating System (ROS)-based mapping method to construct a 3D representation of the environment. Simultaneously, the drone searches for semi-autonomous rough terrain vehicles and semi-autonomous surface vehicles, both on land and in water. The drone utilizes its GPS system to determine the poses of ground and surface vehicles by referencing their positions relative to their own. The ground vehicle then employs a path planner to chart an uninterrupted route to the selected target position on the map.

The framework integrates a neural network-based approach for human and target recognition during exploration. Upon detecting a human or target, the information is relayed to the human rescue team, which approaches a closer view and a 3D reconstruction of the target. This process was repeated as required. The overarching aim of this collaborative strategy is to maximize the computational and onboard sensory capabilities inherent in heterogeneous robot platforms. The complete methodology, seamlessly integrated into the ROS framework, is applicable to any ground-water-aerial multi-robot system, with adjustments tailored to specific requirements.

3.2.1. Communication system

Objective: To establish the communication between the heterogeneous robots for SSRR response.

The BART LAB Rescue Robotics team established a bridging mechanism to facilitate communication between the station and robots by configuring an access point using a Wireless LAN 802.11AC operating at 5 GHz. The default channel is set to Channel 36, but it can be adjusted to any available channel, as needed. As depicted in Figure 8, teleoperated robots are controlled through a wireless LAN 802.11AC connection that enables seamless communication between the operator station and the onboard control system.

Another onboard access point on the robot serves as the interface for receiving commands and transmitting the processed data to the station. These data were collected using USB-connected sensors and devices, including cameras, speakers, microphones, and Hokuyo laser range finders (Hokuyo Automatic Co., Ltd. in Osaka, Japan). Through both USB and serial interfaces, the onboard computer and robot maintained effective communication. Control over propulsion, manipulators, other actuators, and hardware is centralized within an onboard robot central processing unit that employs a feedback control system for operation. Additionally, the robot was equipped with a set of emergency switches designed to shut down or restart the control system.

3.2.2. Graphical user interface

Objective: To develop user-friendly graphical user interfaces (GUIs) for controlling multi-robot SSRR missions.

The effective control of multi-robot SSRR missions depends on the development of user-friendly graphical user interfaces (GUIs). These interfaces empower operators to monitor and control individual robots during search missions, aiming to streamline the management of multiple robots and enhance situational awareness.

Various designs for GUIs catering to the control and information feedback of multiple rescue robot teams have been explored previously [40–44]. The central objective is to furnish operators with a graphical user interface that serves three core purposes: (1) to offer a user-friendly experience, (2) to support the maintenance of situational awareness, and (3) to alleviate operator workload. The interface design incorporates fixed camera views, mapping features, video information, and GPS locations from the heterogeneous robots.

3.2.3. Human/target detection

Objective: Visually identify targets and humans with the ground robot.

In SSRR missions, the detection and identification of objects and targets within the camera frame, along with their classification, are of paramount importance. Object detection platforms often yield results that may not be as conspicuous as those achieved by rescuers. Current detection methods typically involve the extraction of a set of features from input images. These systems perform detection by either focusing on specific regions of the image or by conducting a sliding-window scan across the entire frame.

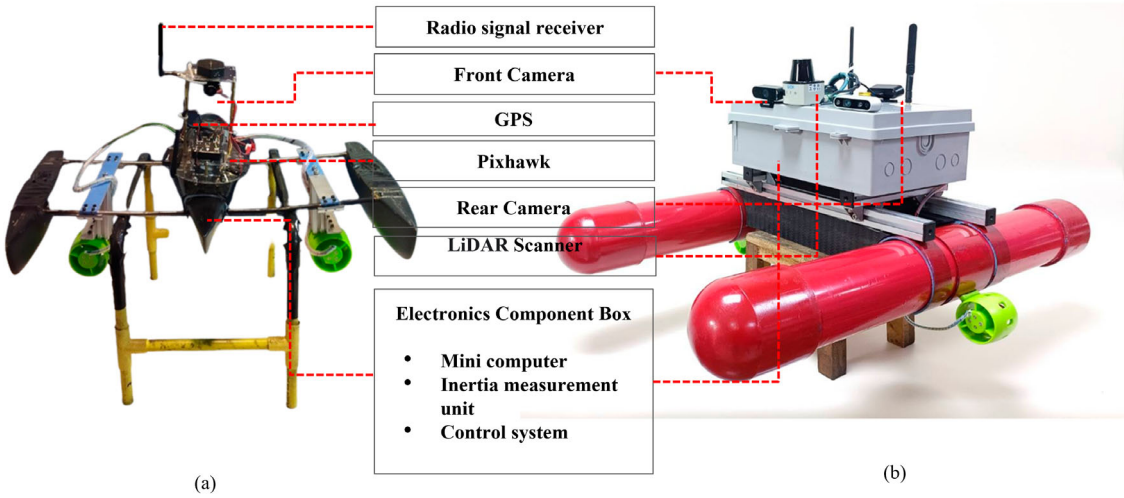


Figure 6. TeleOp/semi-autonomous surface vehicle (a) BL-USV-I, (b) BL-USV-II.

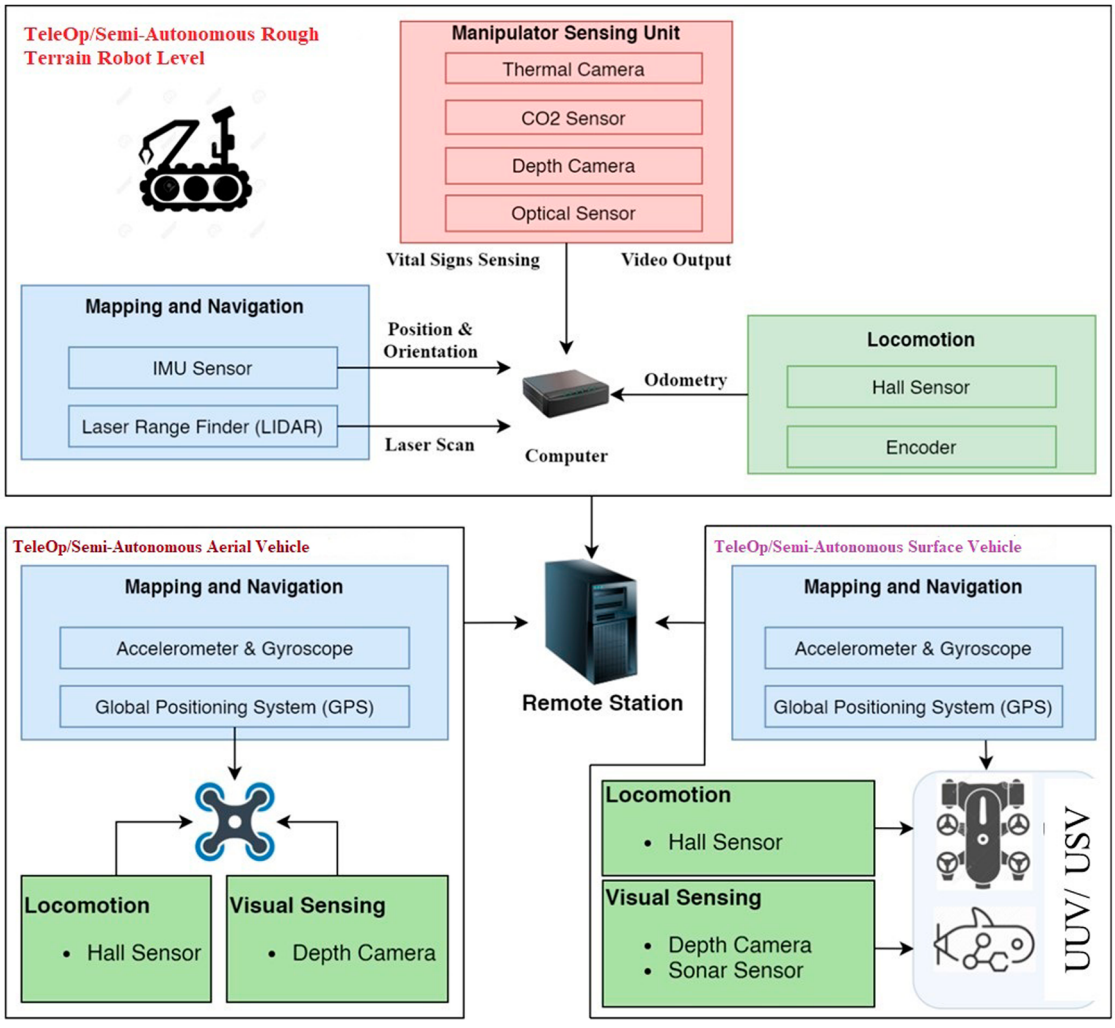


Figure 7. Overview of the collaborative approach's architecture and sensors.

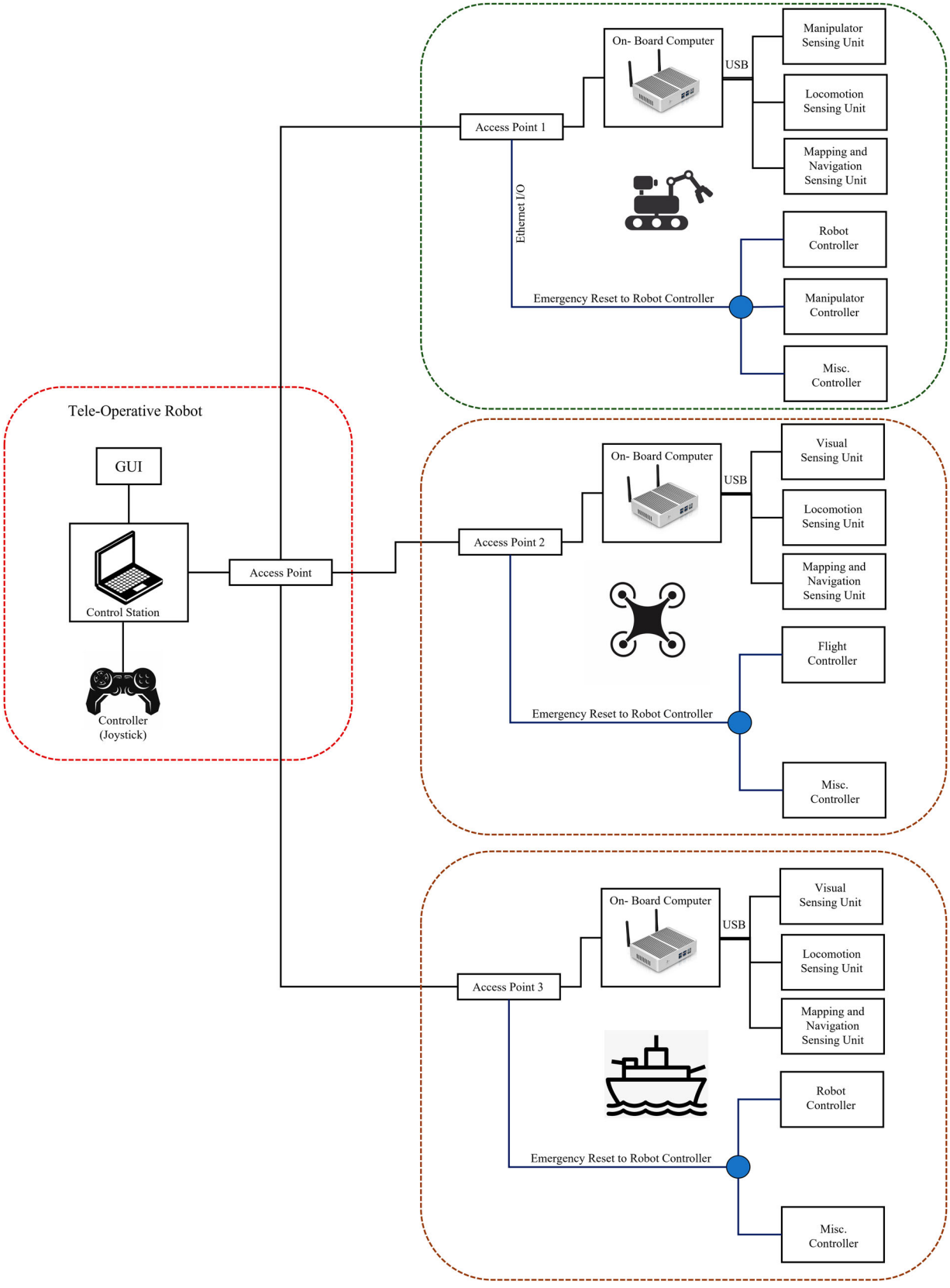


Figure 8. Diagram illustrates the control scheme for communication of the heterogeneous robots system.

To tackle the challenge of target/human detection, we employ TensorRT, a machine learning framework developed by Nvidia (NVIDIA Corporation, Santa Clara, California, U.S.) [45]. TensorRT is specifically optimized for executing machine learning inferences on NVIDIA GPUs. This system simultaneously predicts class probabilities for boxes that encompass any detected objects in the image frame.

3.2.4. Dimensional analysis of objects from 2D image

Objective: Provide a dimensional Analysis of Objects from 2D-Images from a single camera and depth camera.

Generally, the distance of an object from the camera is estimated first, followed by the width is computed using the pinhole projection formula [46] given by (1)

$$w_t = \frac{D_t \times p_w}{f} \tag{1}$$

where,

w_t : Actual width of the target object
D_t : Distance of the target object from the camera
p_w : Pixel width of the object
f : Focal length of the camera

However, when measuring distances or dimensions from an image, these relationships have certain limitations depending on factors such as the drone's altitude and the ground sample distance (GSD) [47]. Therefore, an accurate estimation of the altitude of a drone is essential for precise measurements. To address this, we begin by providing an overview of how the drone altitude, which can be estimated using sensors, plays a crucial role in the process. Figure 9 illustrates the current process flowchart for estimating the region of interest (ROI) and analyzing the dimensions of the objects of interest (OOI) from images in the SSRR missions. Recent advances in drone technology have enabled highly accurate positioning. Although drones are commonly used for aerial photography, many models available on the market can also measure the height or distance between the drone and the ground. An onboard barometer controls flight height by detecting changes in air pressure, and a Vision Positioning System (VPS) calculates the drone's vertical position. The combined use of these sensors results in a more precise vehicle positioning [48,49].

The real distance between two objects, or the dimensions of an object, can be determined from a single image transmitted from the SSRR scenario to the ground station. The data were processed at a ground station to estimate the dimensions. MATLAB (R2020b, Mathworks Inc., USA) line ROIs were employed to measure the distances within the image using pixel values. However,

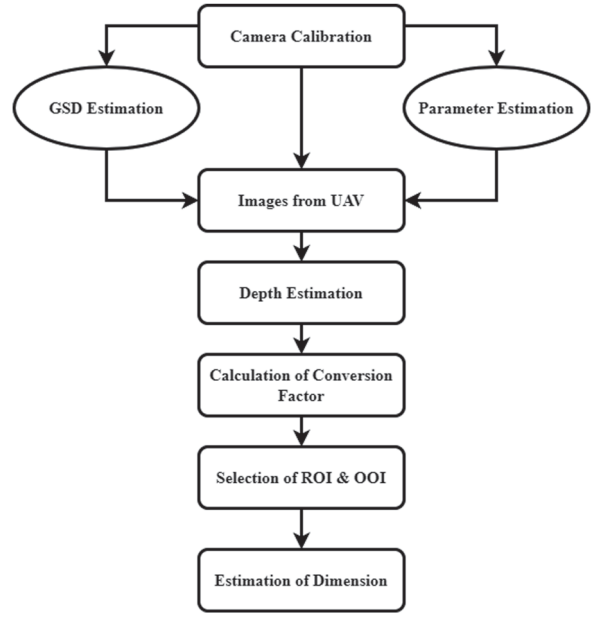


Figure 9. Dimensional analysis process flowchart.

camera calibration is essential to accurately measure the actual distance or dimensions. The estimation of real-world values from images depends on factors such as the distance-pixel ratio, calibrated position of the drone relative to altitude, and pixel distance within the image. The camera's distance–pixel sampling ratio remains constant, allowing for accurate estimations at different heights. This determination was performed by comparing the pixel values to real-world measurements. Therefore, real-world values can be expressed as

$$R_D = K_c P_{DP} D_t D_{Pix} \tag{2}$$

where,

K_c : Conversion constant $K_c = \frac{2.54}{96}$
R_D : Real distance in the global coordinate in cm
P_{DP} : Distance-pixel sampling ratio parameter
D_t : Altitude from the object in cm
D_{Pix} : Pixel value

Geometric camera calibration, also referred to as camera resectioning, is a process that determines the parameters of an image or video camera lens and image sensor. However, it is essential to address the distortion caused by the cameras before estimating these parameters. Intrinsic values can be estimated after the image is undistorted. Parameter P_{DP} can be determined by comparing the known values of R_D, D_t, and D_{pix} of the camera. Notably, the P_{DP} value remained constant throughout the calibration process.

Table 2. Camera calibration.

Images	Distance (cm)	P_{DP}	Mean value of P_{DP}
image 1		0.0114	
image 2	30	0.0115	
image 1		0.0114	
image 2	35	0.0112	
image 1		0.0114	
image 2	40	0.0113	
image 1		0.0115	0.01135
image 2	50	0.0114	
image 1		0.0116	
image 2	150	0.0111	
image 1		0.0112	
image 2	250	0.0113	

The pixel density, measured in dots per inch (dpi), was set to 96 dpi for our images, which means that there were 96 pixels in every inch. To convert this to centimeters, we know that 1 inch is equals 2.54 cm. Thus, there were 96 pixels every 2.54 cm, making the size of one pixel approximately 0.0264 cm (0.264 mm), therefore conversion constant $K_c = \frac{2.54}{96}$. Pixel density, commonly measured in dpi, is a key property of imaging devices such as cameras, scanners, and display media. It can be configured within device settings to meet specific requirements. So, Equation (2) rewritten in (3)

$$P_{DP} = \frac{R_D}{K_c D_t D_{Pix}} \tag{3}$$

The UGV/USV/UAV identifies the target by employing a customized object detection algorithm, captures images of the objects of interest (OOI), and transmits them to the ground station. Subsequently, the ground station calculates the measurements of the OOI dimensions. To facilitate this process, parameter P_{DP} of the vehicle's camera must be determined before the operation commences. The calculation of P_{DP} relies on known values, specifically R_D and D_t, as shown in Table 2. From the measurement of the pixel values using MATLAB line ROIs, they can be converted into real distance values using Equation (2). To ensure the accuracy and reliability of this process, the estimated value of P_{DP} was rigorously verified at six different altitudes, resulting in a value of 0.01135.

An alternative solution, the Intel® RealSense™ Depth Camera, uses various technologies, including stereo vision, time-of-flight (ToF), and structured light, to estimate the depth and volume of objects [50–52]. The Intel® RealSense™ Depth Camera combines these technologies to generate a dense depth map of a scene. This depth map serves as the foundation for estimating the depth and volume of the objects within a scene. The process involves segmenting the objects within the scene based on a depth map, followed by the use of depth information to compute the volume of each object. It is crucial to acknowledge that the accuracy of these depth and volume estimates depends on several factors, including lighting conditions, the surface reflectance of the objects, and the quality of the algorithms deployed for data processing.

The choice of RealSense D435i in the experiment was driven by its compatibility with the research setup. While it is true that the 10-meter range may not suffice for all rescue scenarios, it is important to highlight that this experiment was conducted in a controlled environment. In real-world flood and landslide disaster scenarios, the selection of an appropriate depth camera depends on the specific mission requirements. For our envisioned real-world applications, we would consider employing depth cameras with extended-range capabilities to ensure that the UAV can effectively measure depth from its operational altitude. The choice of depth camera for any mission is tailored to the particular operational requirements and environmental conditions of the disaster site.

3.3. Optimization techniques for unmanned ground vehicles

3.3.1. Energy optimization for path planning and decision making for multiple robots

Objective: Algorithm for determining a suitable robot from a multi-robot system for an instantaneous task during rescue operations.

Rescue robots are often deployed in environments fraught with potential hazards and dangers [53]. Consequently, these robots should exhibit a high degree of autonomy and require minimal human intervention. The power supply is a pivotal factor that influences their performance and mission success. An inadequate power supply can lead to mission disruptions, emphasizing the need for robots to be energy efficient during rescue operations. The significance of minimizing energy consumption becomes evident as it directly impacts task completion and mission success. To address this challenge, it is imperative to assess the energy consumption of the individual robot components and make corresponding estimations and compensations [14,15].

Ground robots employ path-planning algorithms to generate trajectories while navigating through complex terrains and address various challenges, such as 3D navigation, obstacle avoidance, and adaptive path replanning. These path-planning techniques rely predominantly on the position, orientation, and dynamics of the robot. However, a notable limitation of the existing methods is their failure to account for the interplay between path planning and energy consumption. As a

result, there is a compelling need for path-planning algorithms that incorporate considerations of battery performance, particularly for a multitude of unmanned robots. The proposed approach aims to select the most suitable robot for immediate tasks during rescue missions, taking into account the energy-efficient trajectory of each robot within a multi-robot system and continuously monitoring the battery status of each robot [14,15].

The authors have developed an algorithm, and the simulation results [14,15] affirm the efficacy of the proposed energy optimization method in guiding decision-making processes for mobile robots during rescue operations and multi-robot scenarios. Additionally, the method aids in estimating and predicting energy consumption across maneuvering, computing, and sensing processes. An overview of the proposed algorithm and pseudocode is shown in Algorithm – 1 and Figure 10 respectively.

3.3.2. Thermoelectric cooling for rough terrain rescue robots

Objective: A model predictive control-based thermoelectric cooling system for rescue robots in hazardous environmental condition operations.

In the context of rescue operations conducted in hazardous environments characterized by water, dust, toxic gases, or fire, the conventional method of using atmospheric air intake for cooling purposes within the electronic enclosure of rescue robots may prove impractical and potentially detrimental to electronic components [54]. To address the specific challenges encountered by rescue robots, the adoption of thermoelectric cooling systems in real-time rescue scenarios has become highly relevant.

In this scenario, the application of Model Predictive Control (MPC) has been proposed as the optimal temperature control strategy for thermoelectric elements with the objective of reducing energy consumption and operational costs [55]. Experiments have been conducted to examine the feasibility of thermoelectric cooling using MPC-based controllers, particularly in the context of rough-terrain robots [55]. The experimental setup is shown in Figure 11. In this study, a Computational Fluid Dynamics (CFD) approach was meticulously examined and analyzed using the proposed simulation techniques.

4. Results and discussion

To validate the proposed methodology and realize the objectives outlined in the preceding section, we conducted an experimental study encompassing scenarios involving heterogeneous robots.

4.1. Robotic system components and functional elements

The experiments were conducted within the controlled environment of the NIST standard indoor arena and in outdoor settings, seeking to establish its own location and that of the ground-water robot, which was tasked with searching for targets and humans. It was assumed that aerial robots would operate in expansive areas with minimal constraints imposed by the surroundings, except for communication boundaries, including potential challenges such as smoke, wind, or low-light conditions. The drone plays a pivotal role in enhancing situational awareness for other robots within the environment, although the visual detection of small targets across extensive areas poses a significant challenge.

Each robotic system was operated by a distinct operator, which is a common practice to ensure precise control and decision-making tailored to the capabilities of each robot. However, the unique advantage of our integrated system and GUI is that it empowers each operator to efficiently locate, monitor, and coordinate the entire robotic ensemble from the ground station. Through the GUI, every operator gains access to real-time position data and live video feeds from all the robots, facilitating a holistic view of the disaster scenario. This helps different robots work together better during emergencies.

Operating efficiently over long distances while maintaining a high degree of autonomy and ensuring real-time communication is a complex endeavor. The indoor and outdoor search area and experimental setup are illustrated in Figure 12. The drone employed various altitudes ranging from 2.5 to 8 meters in its quest to locate the ground-water robot and the designated targets. While the majority of the experiments were conducted in outdoor environments, selected indoor/outdoor results were included for illustrative purposes, underscoring the versatility and adaptability of the proposed approach in diverse circumstances.

Figures 13 show the experimental setup of heterogeneous robots working in an outdoor environment and the output of the GUI, including real-time video from three robots and the position of the drone. The layout of the interface consists of three windows with real-time video of the ground, drone, and surface vehicle and the live position of the drone.

The neural network, which plays a pivotal role in target and human recognition, was rigorously tested using footage captured by drones and ground vehicle cameras. Impressively, it demonstrated the ability to identify targets and humans, even when they were present in groups, as depicted in Figure 14.

Algorithm 1: Energy-Efficient Algorithm for Rescue Robots

```
Function energy_efficient_algorithm(robots, obstacles)
    for robot in robots do
        battery_status[robot] = robot.get_battery_status();
    for robot in robots do
        shortest_paths[robot] = robot.forecast_shortest_path(obstacles);
    for robot in robots do
        energy_consumption[robot] = robot.estimate_energy_consumption(shortest_paths[robot]);
    for robot in robots do
        obstacle_data[robot] = robot.collect_obstacle_data(obstacles);
    for robot in robots do
        optimal_paths[robot] = robot.predict_optimal_path(shortest_paths[robot], obstacle_data[robot]);
        optimal_energy_paths[robot] = robot.predict_optimal_energy_path(shortest_paths[robot],
          obstacle_data[robot]);
    for robot in robots do
        efficiency_parameters[robot] = robot.calculate_efficiency_parameters(optimal_paths[robot],
          optimal_energy_paths[robot]);
    most_appropriate_robot = None;
    for robot in robots do
        if efficiency_parameters[robot] > efficiency_parameters[most_appropriate_robot] then
            most_appropriate_robot = robot;
    return optimal_paths, optimal_energy_paths, efficiency_parameters, most_appropriate_robot;
```

During the experiment, we employed the *rtabmap_ros* (RGB-D Handheld Mapping) [56,57] framework to create detailed 3D reconstructions of the environment. These reconstructions were generated by integrating the odometry data and RGB-D data obtained from the UGV. Figure 15 presents a compelling visual representation of the 3D reconstructed image acquired within an outdoor environment.

In Figure 16, using Equation (2), the estimated radius of the omni-pipes from the image is 3.14 cm, whereas the actual radius is 3.00 cm. This estimation demonstrated a remarkable 95.54% accuracy. Similarly, the estimated distance from the omnipipe to the surface vehicle amounts to 210.54 cm, and the estimated distance from the safety valves to the surface vehicle is 124.58 cm, showing an impressive accuracy of 99.29% when compared to readings from commercial sensors.

The volume estimation scenario primarily focuses on estimating the volume of a small robot, rather than addressing specific disaster-related tasks (Figure 17). It aims to showcase the capabilities of the proposed methodology using Intel® RealSense™ depth cameras. The experiments were conducted in a controlled environment (BART LAB) to demonstrate the accuracy and feasibility of the volume-estimation approach. The study does not directly relate to real-world disaster scenarios, but serves as a demonstration of the object identification and quantification capabilities of the system.

Regarding the distance between the camera and robot in Figure 17, the close proximity was intentional, as it allowed us to evaluate the system's performance and accuracy in a controlled environment. However, to provide a comprehensive understanding of the capabilities of our method, it is crucial to clarify the accuracy of measurements at various distances. In an outdoor environment, limitations arose due to the challenges of maintaining the drone's position, which constrained real-time volume estimation in rescue scenarios. Therefore, we conducted our experiments in a controlled setting to address these challenges and ensure the accuracy and reliability of our method.

4.2. Optimization results for unmanned ground vehicles

To increase the energy efficiency of a mobile robot in a rescue mission, an algorithm designed to analyze and estimate the energy consumption before making a decision provides a solution to enable energy-efficient strategies. The details of this study are described in detail [15].

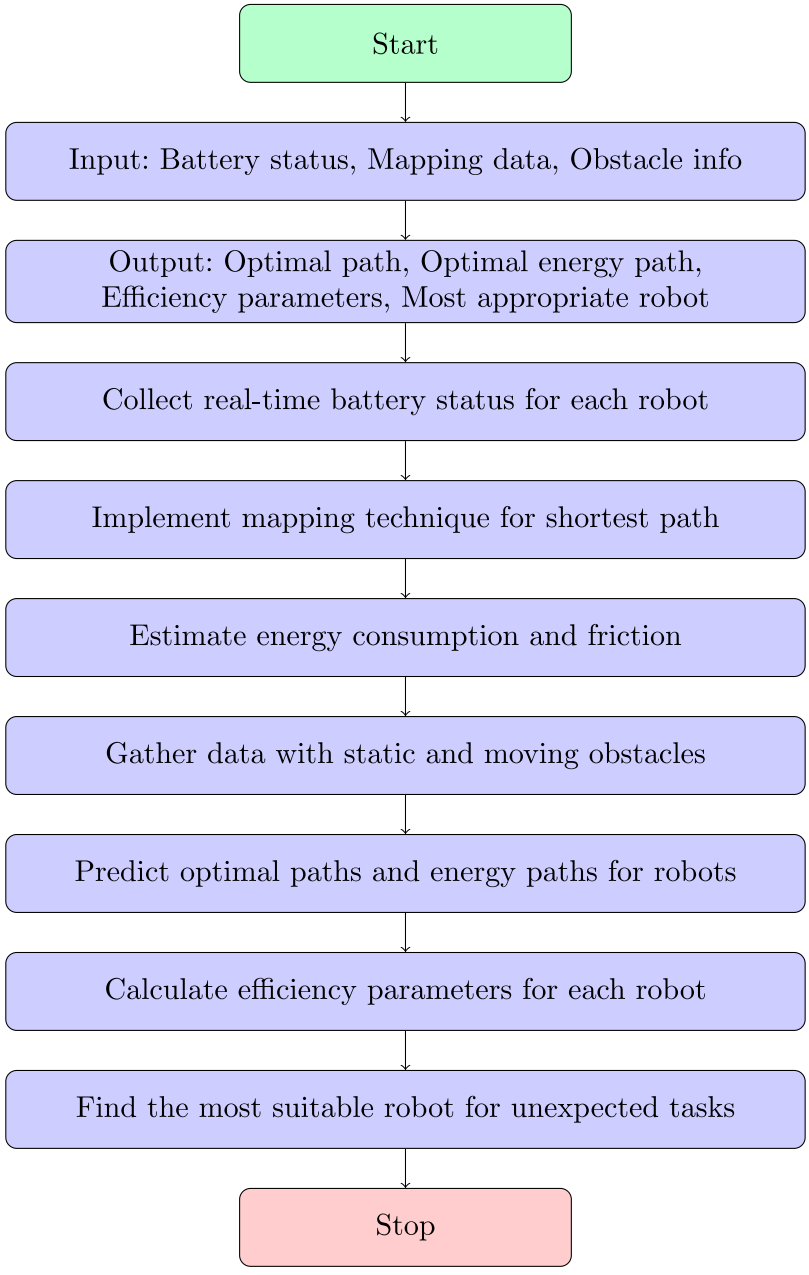


Figure 10. An algorithm for energy-efficient rescue robots in dynamic environments.

Although the simulation results illustrated the feasibility and effectiveness of our proposed algorithm, certain limitations were identified. The experiments were conducted on a 2D plane surface, not encompassing the full spectrum of robot actions such as acceleration, stopping, and movement on various terrains. Furthermore, the time required for the simulation was a concern, particularly in scenarios involving moving obstacles. Nevertheless, our study has provided a vital energy optimization model that predicts energy consumption, supports the analysis of mobile robot energy consumption properties, and enhances decision-making in autonomous rescue operations. Future research should address these limitations by incorporating a more comprehensive experimental field that encompasses all robot actions and terrain variations.

In the case of the Electronic Box, the simulation outcomes showed the intriguing potential of thermoelectric cooling in combination with MPC-based controllers for robots that operate in challenging situations. Two distinct control methods, PID and MPC, were evaluated for temperature regulation in a thermal management system, particularly for rescue robots. The PID controller demonstrated satisfactory control over the temperature and was able to maintain it within the required bounds. However, the simulation revealed a potential drawback – the need for a constant high-energy input–which

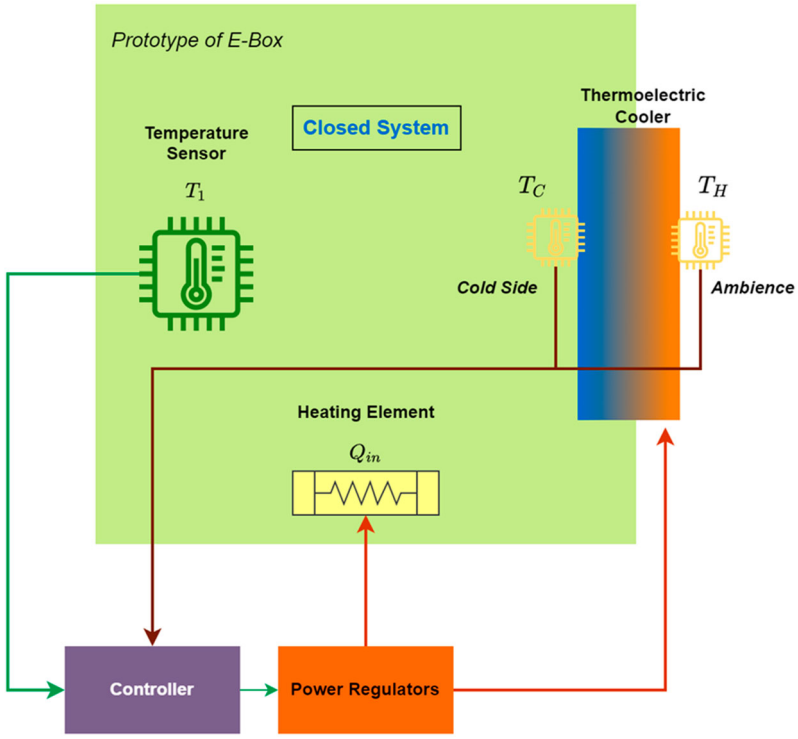


Figure 11. Experimental setup for thermoelectric cooling with MPC-based controllers.

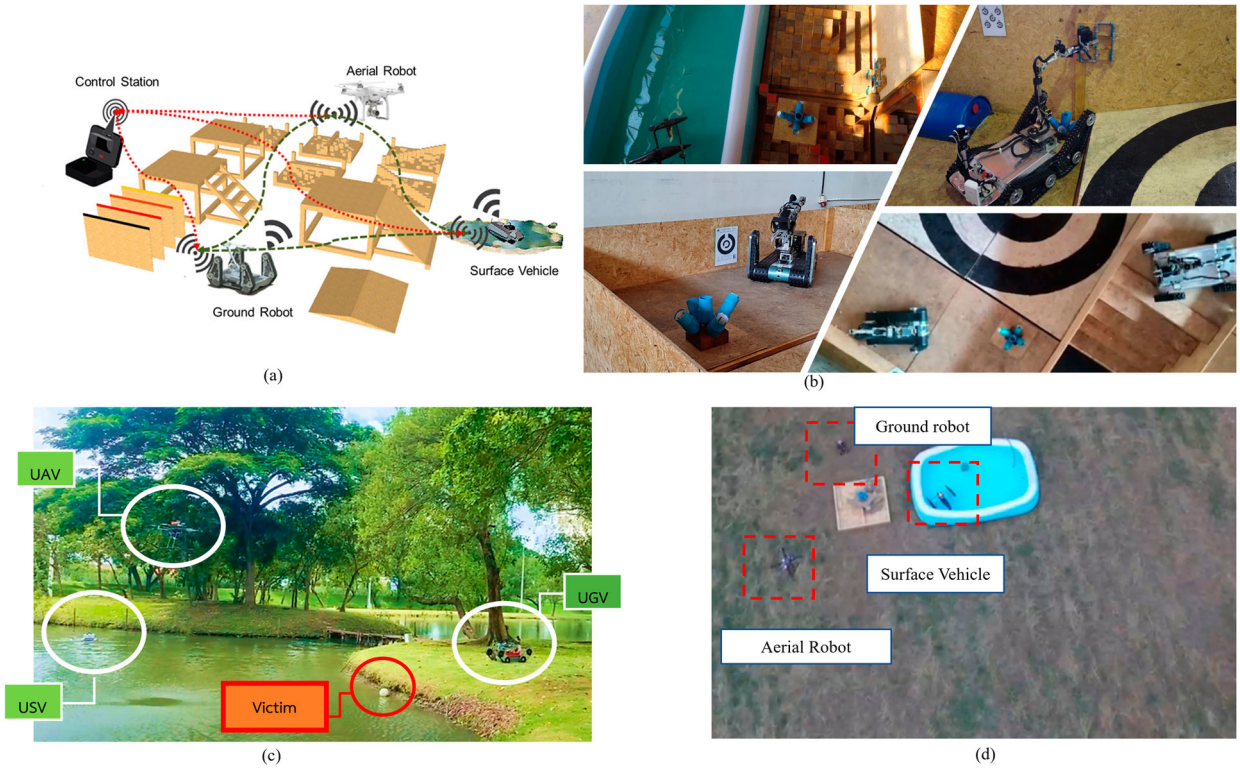


Figure 12. (a) Overview of the NIST standard methods for response robots, (b) Heterogeneous robots working in an indoor environment, (c) Outdoor experimental area-1 (Heterogeneous robots working in an outdoor environment), (d) Outdoor experimental area-2.

could be inefficient for energy-sensitive rescue robots. To address this, MPC was introduced, which showed superior performance in regulating temperature while significantly reducing energy consumption. This allowed the implementation of hard and soft constraints, offering a more efficient solution. Although theoretically challenging, the ease of tuning and reduced energy costs make MPC a favorable choice. Nevertheless, it is essential to acknowledge that practical challenges may arise during the implementation of MPC. This analysis underscores the significance of proper thermal management for robotic systems and the potential advantages of using MPC to optimize energy consumption. For a more comprehensive discussion, readers can refer to the study outlined in [55].

In the conducted experiments, the focus was on three essential areas aimed at enhancing disaster response and safety during floods and landslides. First, a heterogeneous robotic platform was developed to enable multi-robot coordination in complex disaster scenarios. By combining the unique capabilities of these robots, created a comprehensive response system that can navigate diverse terrains, gather real-time data, and reach otherwise challenging locations during such emergencies.

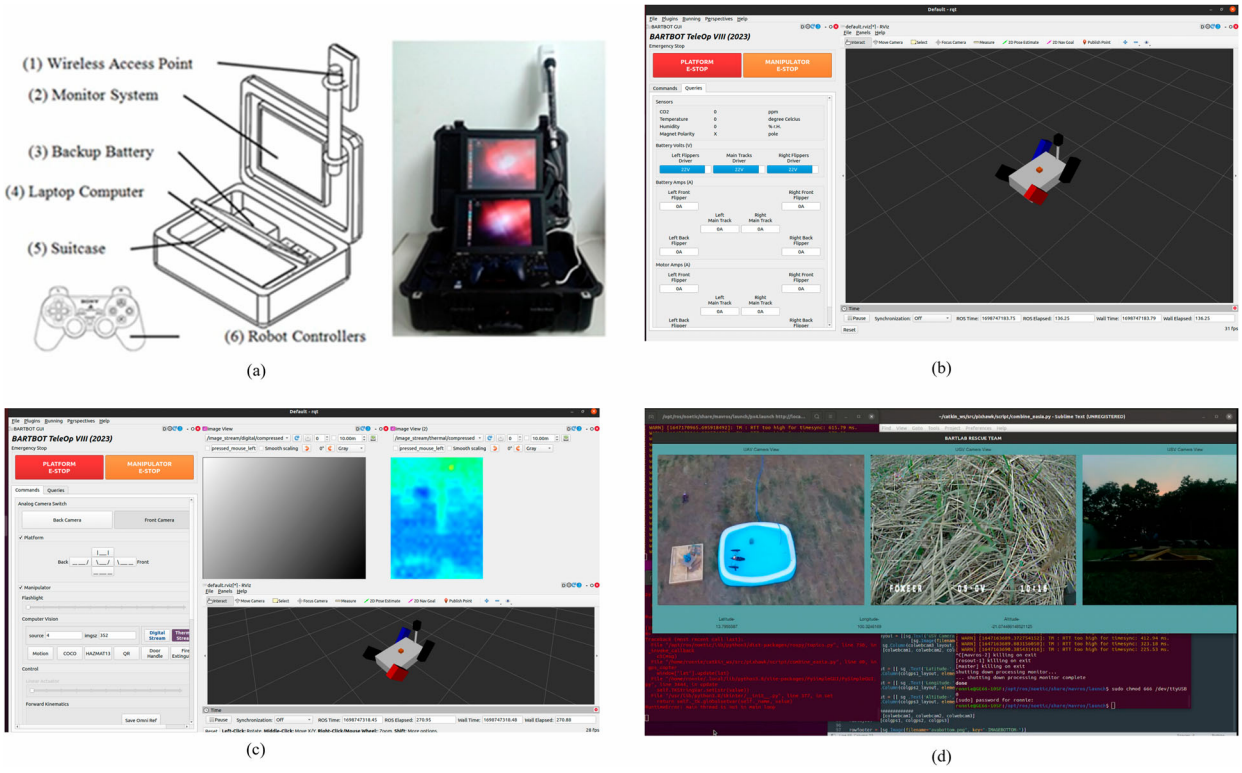


Figure 13. (a) Ground station, (b) Battery status of the Robots in GUI, (c) Camera output in GUI, (d) Output of the GUI: including Real-time video from three robots, and the position of the drone.

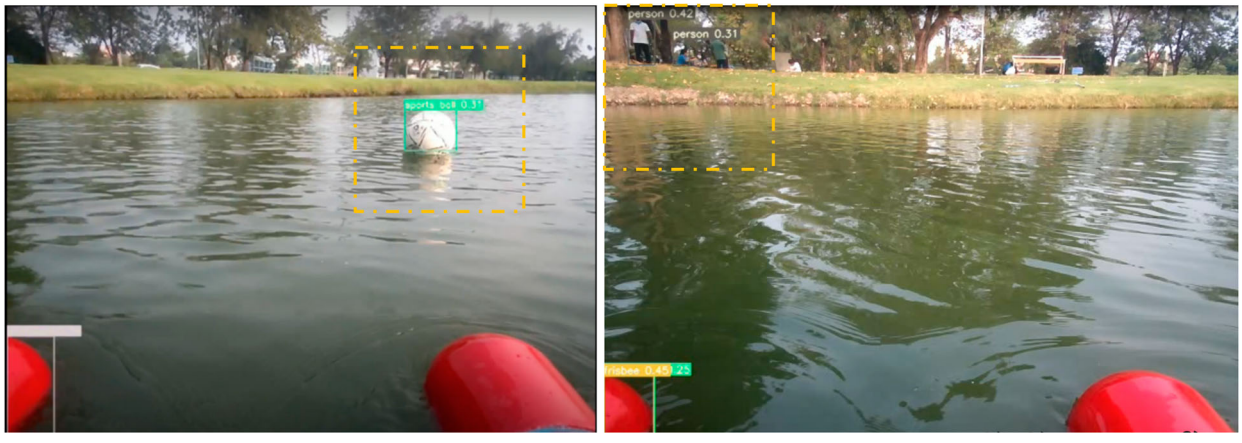
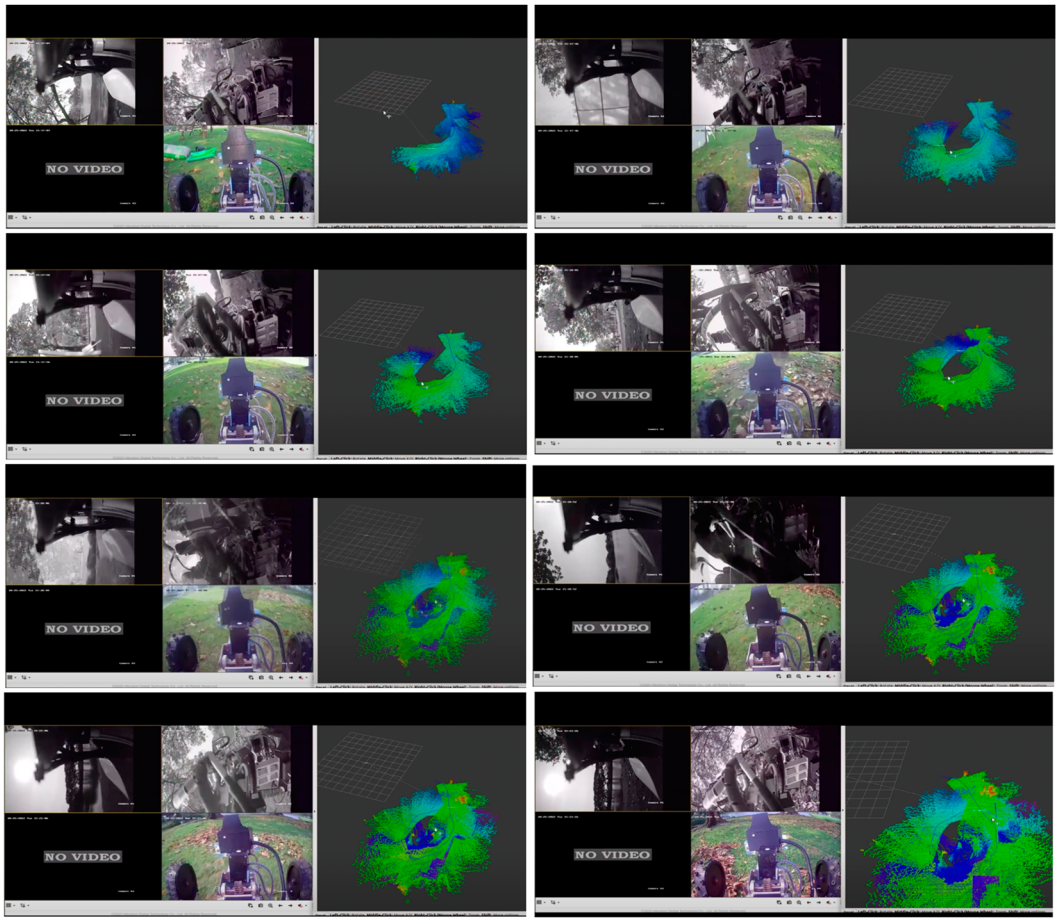
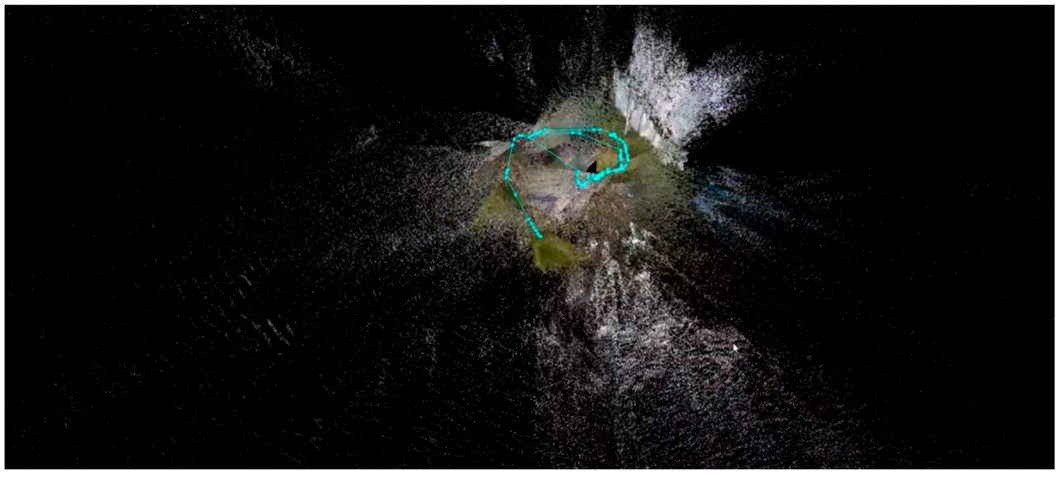


Figure 14. Object detection: target detection from USV.



(a)



(b)

Figure 15. (a) 3D reconstruction of the area during the navigation derived from UGV data, (b) Final 3D reconstructed image obtained from UGV data, showcasing the environment as captured by the robot during its navigation.

Second, critical robotic system components and functional elements were explored, including Communication Systems, Graphical User Interfaces, Human/Target Detection, and Dimensional Analysis, serving as the foundation for efficient communication, control, and information collection. Finally, Optimization Techniques for Unmanned Ground Vehicles are developed, focusing on Energy Optimization and Thermoelectric Cooling. Energy optimization is crucial to ensure that robots can cover larger areas and extend their operational time, thus improving their effectiveness in disaster response. The thermoelectric cooling system is designed to prevent

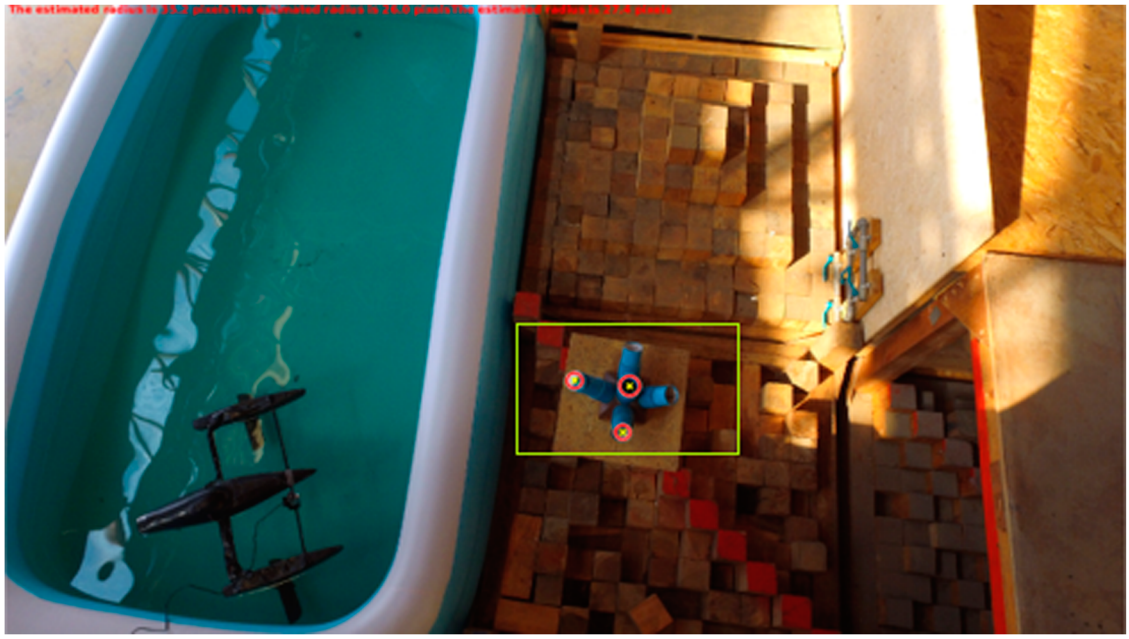


Figure 16. Estimation of the radius of the Omni pipes from the image.

(a) (b)

Figure 17. (a) Calculated the distance between two points using a depth camera, (b) Volume estimation of the object.

the overheating of electronic components under harsh conditions, which can be particularly vital in scenarios involving floods and landslides where water, moisture, and extreme temperatures pose significant threats.

5. Conclusion

This article pointed readers to relevant research papers for more reading by summarizing the initial findings of the Thailand team's successful three-year e-Asia Joint Research Program initiative, including methodologies, models, and algorithms. For the cooperative behavior of heterogeneous robotic teams in sensing, monitoring, and mapping flood and landslide disasters, the project established a framework and control mechanisms. The present study concludes by demonstrating the potential of human-to-human and robot-to-robot collaborations in SSRR applications. The most significant takeaway from this experiment was that robots could work together to achieve challenging objectives by fusing and sharing data to overcome their inherent constraints. Future research will focus on robotic teams building a large collaborative thematic map of a disaster site, which will help human rescue teams expedite the evacuation of survivors from a disaster site and assess the risks of construction collapse and environmental pollution while improving the safety of human rescuers and survivors.

Acknowledgements

The authors express their gratitude to the members of the Center for Biomedical and Robotics Technology (BART LAB)

at Mahidol University for their invaluable support in this research. In particular, the authors would like to acknowledge the outstanding contributions of Mr. Amorchai Khawkhom, whose efforts played a pivotal role in realizing this project. Additionally, special recognition is extended to the dedicated efforts of Pittawat Thiuthipsakul, Korn Borvorntanajanya, Witthawin Sae-Lee, Panuwat Oiamwong, Thitamorn Panyawongngam, Tanadul Somboonwong, Daral Maesincee, Tanapat Thongprong, and Sirikorn Srimuang, whose significant contributions were instrumental in materializing this project. Furthermore, the authors would like to acknowledge the valuable assistance provided by our BART LAB alumni Danial Forouhar and Bibhu Sharma, in the development of the TeleOp-VII and Tanmoy Kumar Das in the creation of the drone and mapping.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research is partially supported by the e-ASIA Joint Research Program Grant through the National Science and Technology Development Agency (NSTDA) and Mahidol University, Thailand [grant number P-19-50869].

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