Air-ground Robotic Collaborative Framework for Autonomous Cramped-space Post-earthquake Search

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Abstract— **After an earthquake, employing robots for search and rescue has become a prevailing trend. However, complex and changing environments, such as composite ruins and limited-space caves, present significant challenges for personnel to approach, making effective plans difficult, and a single type of robot is insufficient given constraints on weight, size, and endurance. To address these issues, an air-ground robotic collaborative framework is proposed. Specifically, a quadruped robot-based recessed helipad structural component with lateral clamping arms is designed for safely and stably on-board manipulation. The quadruped robot carries the drone to the vicinity of the narrow space, and a deep-learning-based perception algorithm is applied to determine whether the drone autonomously launches and continues the inspection. The drone can finally return on its own. The framework is verified through an authentic earthquake training environment, providing promising applications for unmanned search and rescue.**

I. Introduction

Earthquakes often cause building collapses and casualties within moments, leaving survivors trapped deep within narrow and unstable ruins. Extreme site conditions such as aftershocks, toxic gases, and secondary collapses severely restrict human access for search and rescue [1]. In such challenging scenarios, mobile rescue robot systems have emerged as the optimal solution for aiding search and rescue efforts. Nevertheless, not only the unstructured ruins and changing obstacles, but also limited time endurance, load and control radius of the robot, continue to pose severe challenges to search task fulfillment. Large robots capable of overcoming obstacles cannot penetrate confined spaces (such as caves), whereas micro/nano robots suffer from limited endurance. Effective perception and planning of robots in various earthquake scenarios remain under continual development.

In this paper, we conducted systematic and in-depth research on collaborative robot post-earthquake search techniques based on intelligent perception and control [2]. To tackle the composite ruins and limited-space caves, an aerial–ground robotic framework for autonomous post-earthquake search is proposed. The search robots can collaborate and sequentially accomplish visual cave opening detection, autonomous take-off, ingress exploration, image transmission, and autonomous return. Overall, our main contributions are as follows:

1) A helipad of recessed structural component is designed for safely and stably on-board manipulation. With the helipad, a quadruped robot carries a micro/nano AI drone, and the helipad's lateral clamping arms prevent the drone from detachment. Based on the mechanical and electric settings, the quadruped robot can recharge the drone, while the drone can use the robot as a wireless relay for video transmission.

2) An automated workflow of drone launch and landing is proposed. Deep-learning-based perception algorithms, including cave-opening segmentation and downward image recognition are proposed to separately initialize the drone launch and landing.

II. Related Work

A. AI-assisted Active Perception in Search and Rescue

Ali Surojaya et al. [3] develop a deep learning model for visual detection of damaged building openings in real time, considering the scenarios when automated navigation from outdoor to indoor environments. In [4], a You Only Look Once (YOLO) model is introduced to geolocate the fire with stereo vision/epipolar geometry and provides information to the disaster management center via wireless sensor network (WSN). Anh Nguyen et al. [5] propose a multimodal fusion approach to address the problem of autonomous navigation in complex environments such as natural caves.

B. Air-ground Robot Task Planning and Collaboration

I. D. Miller [6] et al. propose a heterogeneous multi-robot system framework where ground robots are able to localize, plan, and navigate in a semantic map created in real time by a high-altitude quadrotor. Similarly, V. D. Sharma et al. [7] consider that the cost map for safe ground robot navigation can be created based on semantic segmentation of the overhead aerial image from a drone. In [8], a UAV and UGV collaborative emergency supplies delivery framework is established for the areas, while the UAV collects visual information about the environment to assist the UGV in reaching the survivors. HMAS (Heterogeneous Multi-Agent Systems) is defined in [9]， where a ROS 2 based software architecture that allows to seamlessly integrate heterogeneous agents and making them interact and collaborate.

III. Framework Overview

When the quadruped robot, carrying the micro/nano AI drone approaches a narrow space, it uses deep learning to assess the size of cave opening and determine whether it is suitable for the drone to autonomously take off. The micro/nano AI drone has the capabilities of autonomous

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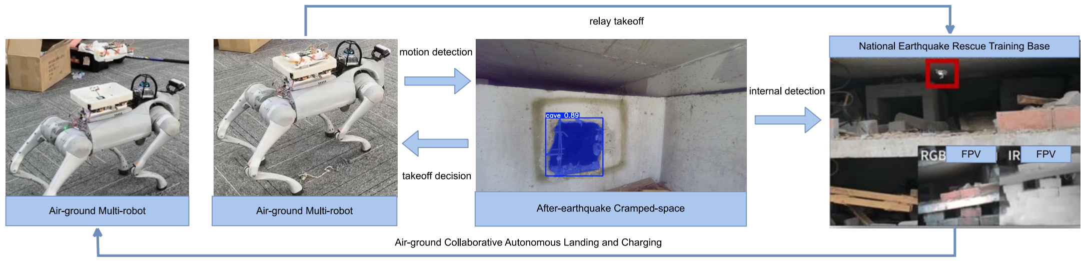


Figure 1. Proposed Framework

patrolling, and autonomous return to land on the helipad located on the quadruped robot's back, while the helipad also supports autonomous charging. As shown in Figure 1.

A. Air-Ground Collaborative Helipad

The air-ground collaborative helipad is mounted on the backplate of the quadruped robot, where the helipad provides landing detection, alignment and clamping functions, and establishes communication and charging with the drone via a magnetic connector.

The structure of the helipad is shown in Figure 2. The helipad is stably mounted to the back rail of the quadruped robot using four fixed seats, and its surface incorporates a recessed section in the design. A pair of photoelectric sensors enables autonomous detection of the drone landing, with a structural design that blocks sunlight interference. Four directional clamping arms are installed on the helipad driven by four clamping motors, which ensure precise alignment and firm fixation of the drone on the helipad.

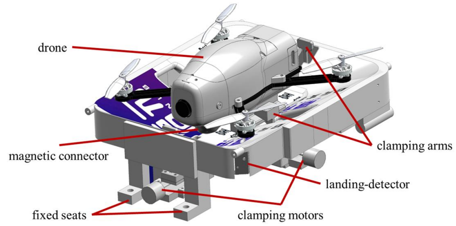


Figure 2. Helipad Appearance and Structure

As illustrated in the front sectional view, the lateral clamping arms provide locking capability in the Z-direction by fitting with the shape of the drone's landing gear, as shown in Figure 3. Once securely clamped, the drone remains safely and stably fixed on the highly mobile quadruped robot without detachment.

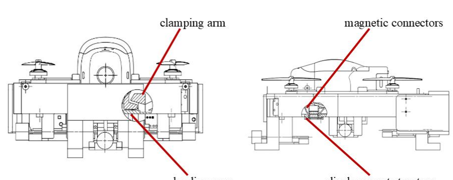


Figure 3. Partial Sectional View of Lateral Clamping Arm and Displaceable Magnetic Connector

The helipad is controlled by an STM32F103 microcontroller from STMicroelectronics, which manages landing detection, clamping motor control, communication between the drone and the helipad, and the charging circuit. A magnetic 5-pin connector provides directional connectivity between the helipad and the drone. Additionally, the helipad includes a micro-displacement mechanism to ensure a stable connection. The functional modules and the task flow diagram of the helipad are shown in Figure 4.

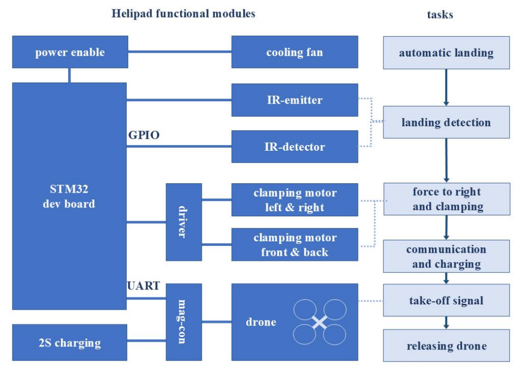


Figure 4. Modules and Task Flow Diagram of the Helipad

B. Quadruped Robot

The quadruped robot in this paper is designed based on the Unitree Go2. When the quadruped robot carries the micro/nano AI drone through the rubble, the obstacle avoidance success rate is no less than 80%, and it can traverse slopes of no less than 35°. A collision occurs, the quadruped robot is designed to recalibrate its path, allowing the robot to continue its mission despite minor disruptions.

C. Micro/Nano AI Drone

The micro/nano AI drone is a self-developed quadcopter weighing 150 g, with a diagonal wheelbase of 176 mm [10]. It is equipped with RGB, thermal imaging, forward multi-point TOF (Time of Flight) LiDAR, lateral/rear/downward single-point TOF LiDAR sensors, and has sensing capabilities of intelligent optical flow with downward recognition. The drone is integrated with a self-developed near-sensor intelligence chip, enabling high real-time multimodal object recognition, monocular depth perception, and autonomous planning algorithms under ultra-low power consumption.

IV. Drone Automatic Launch and Return Control

A. Deep Learning-based Autonomous Takeoff

A YOLOv8-seg [11] perception algorithm is used for target recognition to calculate the opening size of the cave. If the dimensions are smaller than the threshold required for entry, the quadruped robot stops proceeding, triggers the micro/nano AI drone to take off and continue the exploration inside the cave opening. Specifically, when the micro/nano AI drone is ready for takeoff, it first sends a takeoff signal to the helipad, which releases the clamping arms and unlocks the drone.

To prevent misalignment of the labeling frame caused by the non-horizontal orientation of the cave opening, which could lead to inaccurate calculation results, this paper adopts the YOLOv8-seg algorithm for precise recognition and semantic segmentation. After obtaining a segmentation mask that fits the contour more closely, a minimum outer rectangle is calculated to accurately fit the boundaries of the cave entrance, so as to obtain the image pixel coordinates of its four corner points. If any point in the four corners is located at the edge of the image (i.e., the distance from the image boundary is less than the threshold), the detection result is considered incomplete, and it is ignored and the search is continued. The motivation here is safety. we ignore incomplete detections and wait for a reliable one. As long as subsequent frames provide a complete view, detection will succeed. Only in extreme cases (e.g., when the cave is persistently truncated in all frames) may the quadruped robot fail to recognize it. Figure 5 shows the result obtained by using only YOLO and by using fine segmentation respectively. By combining the camera's intrinsic parameters and the depth image, and applying the projection principle, pixel coordinates are transformed into three-dimensional spatial coordinates in real world, so that the actual length and width of the cave opening can be calculated.

Figure 5. Cave Opening Recognition Result

B. Air-Ground Autonomous Landing and Charging

After completing reconnaissance tasks in narrow and obstructed areas, the micro/nano AI drone performs autonomous landing. By reusing the image sensor of the optical flow module, complete black-and-white images of the area beneath the drone can be obtained, with a resolution of 320×240 and a vertical FOV of 80°. When the helipad is level and the drone is in a near-hovering state, the relative position and orientation of the drone with respect to the helipad is determined by identifying the helipad and its LOGO using a YOLO detection algorithm. Using PD control, the drone sequentially performs alignment and positioning, after which it is controlled to land.

With the support of the recessed structure and clamping mechanism, the helipad is capable of realigning and securing the drone when the landing attitude deviation remains within ±30° and the single-axis offset of the landing center does not exceed 0.25m. If the drone's landing position falls outside this tolerance range, successful repositioning may not be achievable. The drone achieves automatic landing through downward-facing recognition. As shown in Figure 6.

When the drone lands approximately at the designated position on the helipad, the helipad's infrared detectors determine whether the drone has landed by detecting the interruption of the transmitted infrared signals. After landing, the four directional motors, arranged in two pairs, forcibly align and clamp the drone. Once the clamping arms reach the locking position, the helipad performs a communication handshake with the drone via magnetic connectors to ensure that the drone on the helipad is the designated one and that it has been securely clamped. Upon successful handshake confirmation, the helipad activates the charging function by controlling a relay in the charging circuit to establish the electrical connection.

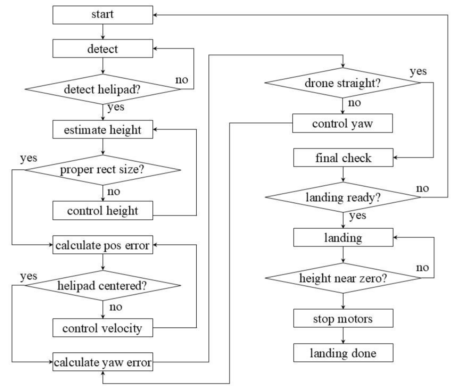
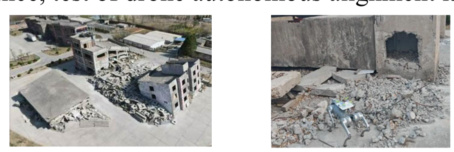


Figure 6. Autonomous Landing Workflow

V. Experiment

Experiments were conducted at the National Earthquake Rescue Training Base located in the Fenghuangling area of Haidian District, Beijing, China, shown in Figure 7(a). In the Figure 7(b), the quadruped robot autonomously traverses the on-site ruins, avoids obstacles and carries the micro/nano AI drone to an exposed open cave. Experimental verification was conducted on two aspects: cave recognition and takeoff performance, test of drone autonomous alignment landing.



(a) Panoramic view (b) An exposed open cave
Figure 7. Experiment Circumstances

A. Cave Recognition and Takeoff Performance

To verify the performance of the autonomous takeoff decision-making algorithm, this paper compares two approaches: **YOLOv8-Seg** and **(YOLO + SAM** [12]**)**.

The training dataset contains 1,713 real-world images of cave opening in earthquake, while the test set consists of 396 images. The evaluation is conducted from three aspects: CPE(Corner Point Error), IoU, and IS(Inference Speed). The CPE refers to aligning the four corner points of each predicted cave opening bounding box with those of the manually annotated box, and calculating the MSE in pixels to assess the spatial accuracy of the extracted corner points.

TABLE I. Comparison of Recognition Algorithms

	CPE	IoU	IS(fps)
Yolov8-seg	50.37	0.7079	0.138
Yolov8+SAM	53.28	0.7099	0.157

As shown in Table 1, YOLOv8-Seg exhibits slightly better boundary fitting and faster inference speed, offering a clear advantage in terms of timeliness for real-world rescue.

TABLE II. Results of 10 Drone Autonomous Alignment Landing Tests

	1	2	3	4	5	6	7	8	9	10	RMS	Mean ± Standard Deviation
x_A	0.37	0.19	0.29	0.38	0.23	0.42	0.47	0.32	0.37	0.31	0.3445	0.335 ± 0.085
y_A	0.11	0.14	0.13	-0.21	0.06	-0.15	0.03	0.04	0.31	0.19	0.1592	0.065 ± 0.153
x_B	-0.25	-0.46	-0.37	-0.29	-0.42	-0.24	-0.19	-0.33	-0.24	-0.35	0.3247	-0.314 ± 0.087
y_B	-0.07	0.23	0.06	-0.16	0.14	-0.13	0.05	0.13	0.08	0.19	0.1362	0.052 ± 0.133
θ	16.2	-7.9	6.1	-4.3	-7.0	-1.7	-1.7	-7.9	20.7	0.0	9.6241	1.25 ± 10.059
t_x	0.06	-0.14	-0.04	0.05	-0.10	0.09	0.14	-0.01	0.07	-0.02	0.0839	0.01 ± 0.088
t_y	0.02	0.19	0.10	-0.19	0.10	-0.14	0.04	0.09	0.20	0.19	0.1407	0.06 ± 0.134

B. *Test of Drone Autonomous Alignment Landing*

The drone is controlled to hover at an altitude of 1m with a random initial orientation. After the test begins, the drone is commanded to autonomously descend onto the target paper, and the positions of two fixed points A and B on either side of the drone are recorded on the paper. When the drone lands at the center of the helipad, the ideal landing coordinates of points A and B are denoted as (x_{A0}, y_{A0}) and (x_{B0}, y_{B0}), while their actual landing coordinates are denoted as (x_A, y_A) and (x_B, y_B). Accordingly, the angular deviation θ between the actual and ideal landings, as well as the center offset vector (t_x, t_y), can be calculated as follows.

$$\theta = \tan^{-1}\frac{(x_{B0}-x_{A0})(y_B-y_A)-(x_B-x_A)(y_{B0}-y_{A0})}{(x_{B0}-x_{A0})(x_B-x_A)+(y_{B0}-y_{A0})(y_B-y_A)}$$

$$\begin{cases} t_x = \bar{x} - \bar{x}_0\cos\theta + \bar{y}_0\sin\theta \\ t_y = \bar{y} - \bar{x}_0\sin\theta - \bar{y}_0\cos\theta \end{cases}$$

The parameters marked with a bar represent the average values of the corresponding parameters of points A and B. The initial coordinates of the fixed points A and B are (0.33, 0) and (−0.33, 0), respectively. The actual landing coordinates obtained from ten test trials, along with the corresponding angular deviations (in degrees, with counterclockwise defined as positive) and center offset vectors (in meters), are summarized in the Table 2.

Experiment proves to use autonomous landing algorithm satisfies the requirements of the landing attitude deviation within ±30° and the single-axis offset of the landing center within 0.25m. With the helipad's realignment capability, drone landing within this range can be correctly clamped.

VI. Conclusion

An air-ground robotic collaborative framework for autonomous post-earthquake search in cramped-space scenario is proposed. A quadruped robot carries a micro/nano AI drone by a specially designed the helipad to the vicinity of the narrow space safely and stably. Deep learning-based perception is used to help determine whether the autonomous take-off and landing conditions for the drone are met.

The proposed recessed helipad, perception modules, and validated quadruped mobility also provide a solid basis for extension to mobile manipulators. The docking interface and communication handshake can support lightweight arm attachment, while the YOLOv8-Seg detection and visual recognition algorithms are transferable to grasp planning and contact alignment. Challenges such as payload-induced dynamics, compliance control, and perception in dynamic rubble environments remain. We will next evaluate a manipulator-equipped quadruped in simulation and field test.

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