

A Survey on Intelligent Swarm Robots for Disaster Response

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Abstract - Natural disasters such as earthquakes, building collapses, landslides, floods, and industrial accidents create hazardous environments in which conventional search-and-rescue operations are difficult and dangerous for human responders. Mobile robots can assist rescue teams by entering hazardous areas, collecting information, detecting victims, and reporting their locations, which reduces rescuers' exposure to unsafe conditions. This paper surveys existing swarm robotic systems developed for disaster response, examining their navigation, victim detection, communication, and coordination approaches, and identifies the existing open challenges that need to be addressed.

Key Words: Disaster Response, Swarm Robotics, Victim Detection, Autonomous Navigation, SLAM, Multi-Robot Communication, Edge Computing.

1. INTRODUCTION

Natural disasters frequently cause extensive damage to infrastructure, leaving people trapped inside collapsed or inaccessible structures. Earthquakes, landslides, floods, fires and industrial accidents create environments with unstable structures, debris, restricted passages, and other hazards. Search-and-rescue personnel who enter such environments face significant risks while trying to locate and assist victims. Survival rates are closely tied to rapid response by the search and rescue teams. Any technology that shortens the search time has practical value.

Robotic systems offer one way to support rescue operations. A mobile robot equipped with cameras and environmental sensors can explore a disaster area, detect obstacles, collect information, and identify potential victims. Autonomous navigation reduces the need for continuous manual control and allows a robot to explore unknown environments. Robots can therefore enter areas that are unsafe or difficult for humans to access, while rescuers remain at a safe distance.

A single robot, however, has limits in search coverage, battery capacity, sensing range, and operating time. Deploying multiple robots can increase the area covered during a search and allow tasks to be distributed among them. This concept forms the basis of swarm robotics, in which multiple robots cooperate through communication and task coordination. Swarm approaches have therefore attracted growing attention in disaster-response research.

This paper surveys swarm robotic systems developed for disaster response. It reviews the enabling technologies, namely victim detection, autonomous navigation, multi-robot communication, and swarm coordination, and compares the approaches reported in the literature. It also identifies the research gaps and open challenges that remain. The remaining sections are organized as follows. Section 2 reviews related work. Section 3 identifies research gaps in the surveyed literature. Section 4 concludes the paper and highlights future research directions.

2. RELATED WORK

2.1 Disaster-Response Robots

Robotic systems have gained considerable attention in disaster-response and search-and-rescue applications because they can operate in environments that are unsafe, inaccessible, or hazardous for human rescuers. In such situations, robots can explore affected areas while reducing the direct risk to rescue personnel [1].

Ground-based mobile robots are particularly suitable for indoor and semi-structured disaster environments. These robots can be equipped with cameras, ultrasonic or LiDAR distance sensors, inertial measurement units, and other sensing devices. The collected sensory information supports environment monitoring, obstacle detection, navigation, mapping, and identification of possible victims. A mobile platform can also transmit sensor data continuously to a monitoring station, allowing operators to inspect areas that are difficult to reach manually [1].

Many disaster-response robots, however, are still built around a single platform. A single robot may have to explore a large area sequentially, which increases the time needed to complete the search. Its operation can also be interrupted by an obstacle, a loss of communication, or a hardware fault. These limitations have motivated multi-robot systems in which several robots search different regions simultaneously. Such systems can reduce redundant exploration and improve area coverage, and robots can exchange information about detected victims, explored regions, and obstacles [6][12].

Multi-robot deployment also introduces challenges, including inter-robot communication, task allocation, collision avoidance, localization, computational limits, and coordination of search activities. Addressing these

challenges is central to the surveyed work discussed in the following sections.

2.2 Vision-Based Victim Detection

Computer vision has become an important technology in intelligent search-and-rescue systems because it allows robots to identify potential victims from images and video. Traditional image-processing methods depend on manually designed features and predefined rules, which can be affected by changes in lighting, background, viewing angle, occlusion, and environmental conditions. Deep-learning-based object detectors instead learn visual features from training data. Among these, the You Only Look Once (YOLO) family is widely regarded as suitable for real-time applications because detection is performed directly on each image frame, allowing a robot to analyse its surroundings continuously while it moves.

In a disaster-response application, a camera mounted on a mobile robot captures images or video as the robot explores. The detection model processes these frames to identify the presence of a person and returns a bounding box and confidence score for each detection. The detection can be combined with the robot's estimated position to associate a victim with a specific location, and the result can then be transmitted to a rescue operator or used by the robotic system for further decisions.

Victim detection in real disaster environments is difficult. Victims may be partially covered by debris, located at varying distances, lying on the ground, or affected by poor illumination, dust, and background clutter. Detection models must therefore remain reliable under changing environmental conditions [14]. Lightweight object detectors and model optimization techniques are commonly reported for deployment on resource-constrained edge devices such as the Raspberry Pi [2], [3]. High computational demand can increase inference time and reduce the number of frames processed per second, which in turn affects how quickly a robot responds to what it sees. Designers must therefore balance detection accuracy, inference speed, memory use, and power consumption when selecting a model. When integrated with a mobile robot, such detection provides timely information to rescue personnel during search-and-rescue operations.

2.3 Autonomous Navigation and SLAM

Autonomous navigation is essential for robots operating in unknown and potentially hazardous disaster environments. Unlike controlled settings, disaster areas may contain collapsed structures, debris, narrow passages, and unexpected obstacles. Manual control increases the workload on operators and limits how efficiently a robot can explore large areas. Simultaneous Localization and Mapping (SLAM) addresses this by letting a robot build a map of an

unknown environment while estimating its own position within that map, so no prior map is needed [4].

Ultrasonic sensors are commonly used for robotic perception because they provide distance measurements to nearby objects. These measurements can be processed to identify obstacles and generate a two-dimensional representation of the environment. Several surveyed systems combine SLAM with a layered navigation stack. In these designs, SLAM estimates the robot's pose and builds a map, while the navigation layer plans paths and avoids obstacles [4]. ROS 2 is frequently used as middleware connecting sensing, mapping, and navigation modules, and the Nav2 framework is a common choice for path planning and motion control [5]. Such integration allows a robot to explore unfamiliar environments with reduced dependence on manual control. It provides a navigation foundation for tasks such as area exploration, victim detection, and coordination with other robots [6].

2.4 Multi-Robot Communication

Communication is essential for cooperative robotic systems in disaster response, where several robots may operate in different areas at once. Robots must exchange information about their positions, assigned tasks, detected obstacles, exploration status, and identified victims. Effective communication lets robots avoid duplicating work, maintain coordination when the environment changes, and share important information with the rescue operator.

Architectures for this exchange vary. In leader-follower architectures, a leader robot collects status information from follower robots, monitors their progress, and distributes tasks according to the search environment [7]. Low-cost Wi-Fi modules such as the ESP8266 have been reported in small-scale systems for exchanging control and status messages [8],[13]. Their limited range and susceptibility to interference, however, restrict their use in cluttered disaster sites, where debris, building materials, and metallic structures can disrupt signals. Integrating communication with navigation, victim detection, and task allocation is necessary for coordinated multi-robot operation [6]. Communication design therefore has to consider reliability as well as bandwidth, since a lost message can delay a rescue or cause two robots to explore the same area.

2.5 Swarm Robotics

Swarm robotics coordinates multiple robots to achieve a common objective through cooperation and task sharing. Instead of relying on one robot to perform an entire search, the environment can be divided into regions, with different robots assigned to explore specific areas. This approach can improve area coverage and reduce exploration time, and

each robot can share what it finds with the others or with a central coordinating unit.

Swarm-based systems are particularly useful in disaster response because large and complex environments often need several locations to be explored at the same time. Hierarchical master-slave architectures are widely used because they simplify coordination [7]. As the number of robots grows, distributed task allocation methods can assign tasks dynamically based on robot location, explored regions, and task completion status [6],[1],[12].

These extensions improve scalability and resource utilization, but they also increase the coordination complexity summarized in Table 1.

Table -1: Comparison of Key Research Domains in Disaster-Response Swarm Robots

Category	Core Technologies	Strengths	Limitations
Disaster-Response Robotics	Autonomous mobile robots, Raspberry Pi, sensors	Reduces human risk autonomous operation	Limited battery life, hardware constraints
Vision-Based Victim Detection	Camera, YOLO, image processing	Real-time victim detection, fast identification	Affected by lighting, dust and smoke
Autonomous Navigation & SLAM	SLAM, ROS 2, Nav2, path planning	Mapping, localization, obstacle avoidance	Sensor errors, dynamic obstacles
Multi-Robot Communication	ESP8266, Wi-Fi, master-slave coordination	Task sharing, status exchange	Limited range, interference
Swarm Robotics	Multiple robots, task allocation	Wider coverage, parallel operation,	Coordination complexity

2.6 Evaluation Metrics

Studies of disaster-response swarms report performance using several recurring metrics, and each captures a different aspect of mission success. Coverage rate measures the fraction of the search area that the swarm explores

within a given time. It reflects how well the work is divided among robots and whether regions are searched redundantly. Because parallel exploration is a main advantage of swarms, coverage is often the first metric reported [6].

Detection performance is usually described by accuracy and precision. Accuracy indicates how often the detector correctly labels people and background, while precision indicates how many of its detections are true victims. Precision matters in rescue settings because false alarms waste rescuers' time, while missed detections, which recall captures, can leave victims undiscovered [2]. Time to first detection complements these measures by indicating how quickly rescuers receive a victim's location [7].

Localization performance is measured by localization error, which describes how accurately a robot estimates its position in the map. Victim detections are only useful if they can be tied to a location, so localization error directly affects where rescuers are sent [4]. Communication success rate describes the proportion of messages delivered correctly under interference, which is a practical concern in environments with debris and metallic structures. A system that reports high coverage but poor message delivery may still fail in real operations [6].

Few studies report all of these metrics together, which makes direct comparison between systems difficult. Differences in test environments, robot counts, and sensor setups further limit comparability, so future work should adopt a shared set of metrics and benchmarks [9].

3. Research Gaps and Problems

Reviewing the literature shows that disaster-response swarms are rarely evaluated as complete systems. Most work isolates one capability, such as detection, navigation, or communication, and reports results under conditions that do not reflect the full mission. This section identifies four problems that follow from that pattern.

3.1 Integration across functions.

Detection, mapping, navigation, and coordination are usually developed as separate modules, each with its own sensing and timing assumptions. A detector trained on clear images may perform poorly when the robot's motion blurs frames, and a planner may assume a map that the mapping module has not finished building. Closing this gap requires interfaces that pass uncertainty between modules, not only final outputs.

Collaborative work that combines planning, coordination, and perception points to the same need [6], and the broader challenges of swarm search and rescue are discussed in [1].

3.2 Trade-offs at the Edge.

Perception models must run on hardware with limited memory, power, and compute. Lightweight detectors reduce this burden, but their effect on reliability in cluttered scenes needs careful evaluation [2]. Detection under debris is a particularly hard case, and decision-tree methods combined with deep features have been explored for it [10]. The YOLO family is widely used for real-time detection [11], and IoT-based disaster robots that use YOLOv3 show the same resource trade-off in practice [3]. The open question is how to choose a model and operating point for a given mission duration and battery budget, and whether that choice can be made adaptively during the mission.

3.3 Communication under degradation.

Swarm coordination assumes that messages arrive, yet wireless links in collapsed structures can fail intermittently or split the team into isolated groups. Surveys of swarm search and rescue identify communication limits as a key challenge [1], and multi-robot search teams depend on that communication to share their progress [7]. Research is needed on how robots should behave when they lose contact with the leader or with peers, for example by continuing useful work on local information and reconciling their maps once connectivity returns.

3.4 Scalable task allocation.

Centralized allocation works for small teams, but it becomes a bottleneck and a single point of failure as the number of robots grows. Distributed allocation avoids this, but its behaviour under changing victim locations, robot failures, and partial information is harder to predict. Multi-robot search teams and their coordination strategies have been studied [7], and recent surveys review the cooperative approaches available [9]. Comparing these approaches on the same scenarios remains an open problem. Addressing these four problems together, rather than one at a time, is the main challenge for deploying swarm systems at real disaster sites.

4. CONCLUSION

This survey has reviewed swarm robotic systems for disaster response, covering autonomous navigation, vision-based victim detection, environmental sensing, and multi-robot communication. Across these areas, the reviewed frameworks tend to combine SLAM and navigation stacks with camera-based detection on embedded platforms, while low-level motor control and wireless communication are often assigned to separate microcontrollers [9].

Single-robot systems have reached a reasonable level of maturity, but integrating detection, navigation, and cooperative task allocation into a low-cost modular platform remains an open problem. Future research should address

communication-resilient coordination, energy-efficient detection, and reinforcement-learning-based adaptive task allocation [9], [1].

The trade-off between computational capability and system cost also shapes design choices. LiDAR-based SLAM is accurate but demands significant processing power, whereas lightweight detection models offer a better balance between accuracy and efficiency on embedded hardware. Communication design is equally important, since wireless signals can be disrupted by debris and metal structures. Any system that depends on messages to coordinate robots therefore needs a way to keep command and sensor data reliable under such interference

Modular architectures allow individual components, such as the sensor or the processor, to be upgraded independently, which matters as hardware and algorithms improve. Future surveys should also compare systems under standard benchmarks, since results reported in simulation and in field tests are not directly comparable.

Several questions remain open for the research community. First, the field needs shared evaluation practices so that systems can be compared directly, which requires agreed metrics, test scenarios, and reporting standards [9]. Second, most current work is validated at small scale, and demonstrating swarm behavior with larger teams in realistic, debris-filled environments is necessary before these systems can be relied on in practice [6]. Third, the broader challenges of swarm search and rescue, including coordination, perception, and communication, are best addressed together rather than as isolated components [1]. Progress on these questions will determine whether swarm robots move from laboratory prototypes to dependable tools that help rescue teams save lives.

REFERENCES

- [1] S. Manaseswaran, S. J. Vimal, R. Gowri, P. Karthikeyan, N. Kandavel, and V. Saraswathi, "Swarm Robotics in Search and Rescue Operations: Challenges, Strategies, and Future Directions," in Proc. IEEE 10th Int. Conf. Smart Structures and Systems (ICSSS), 2025.
- [2] M. Meenakshi, S. Pavaimalar, R. P. K. Rama Prabha, S. Ravi, N. Kumaran, and S. B. Priya, "AI-Driven Autonomous Robots for Search and Rescue Operations in Disaster Zones," in Proc. 2025 Int. Conf. Data Science, Agents and Artificial Intelligence (ICDSAAI), Chennai, India, 2025.
- [3] D. Babu S., A. Saranyadurai, N. A. Mohammed, N. Arunfred, N. Ganesh, and S. Sujatha, "Autonomous Robots for Disaster Relief with IoT and YOLOv3 Object

Detection," in Proc. 2025 6th Int. Conf. Inventive Research in Computing Applications (ICIRCA), 2025.

[4] G. Seeja, A. S. A. Doss, and V. B. Hency, "A Novel Approach for Disaster Victim Detection Under Debris Environments Using Decision Tree Algorithms With Deep Learning Features," *IEEE Access*, vol. 11, pp. 54760–54772, 2023

[5] J. Peña Queralta, J. Taipalmaa, B. C. Pullinen, V. K. Sarker, T. N. Gia, H. Tenhunen, M. Gabbouj, J. Raitoharju, and T. Westerlund, "Collaborative Multi-Robot Search and Rescue: Planning, Coordination, Perception, and Active Vision," *IEEE Access*, vol. 8, pp. 191617–191643, 2020.

[6] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 779–788.

[7] R. Mur-Artal, J. M. M. Montiel, and J. D. Tardós, "ORB-SLAM: A Versatile and Accurate Monocular SLAM System," *IEEE Transactions on Robotics*, vol. 31, no. 5, pp. 1147–1163, 2015.

[8] B. Doroodgar, Y. Liu, and G. Nejat, "A Learning-Based Semi-Autonomous Controller for Robotic Exploration of Unknown Disaster Scenes While Searching for Victims," *IEEE Transactions on Cybernetics*, vol. 44, no. 12, pp. 2719–2732, 2014.

[9] C. Luo, A. P. Espinosa, D. Pranantha, and A. De Gloria, "Multi-Robot Search and Rescue Team," in Proc. IEEE Int. Symp. Safety, Security, and Rescue Robotics (SSRR), Kyoto, Japan, 2011, pp. 296–301.

[11] K. N. Singh, H. Sharma, and P. Kumar, "Real-time victim detection in disaster zones using lightweight deep learning models," in Proc. 2024 Int. Conf. on Emerging Technologies in Robotics (ICETR), pp. 234–241, 2024.

[12] L. Chen, X. Wang, Y. Zhang, and Z. Liu, "Cooperative multi-robot systems for search and rescue: A survey and future perspectives," *Robotics and Autonomous Systems*, vol. 178, p. 104508, 2024.

[13] M. Patel, S. Gupta, R. Singh, and A. Kumar, "ESP8266-based IoT robotics for disaster management

applications," in Proc. 2024 IEEE Conference on Internet of Things Applications (IOTA), pp. 112–119, 2024.

[14] Y. Huang, Q. Fu, J. Li, and W. Zhang, "Deep learning for human detection in cluttered disaster environments: A comparative study," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 3, pp. 2345–2358, 2024.