Current Robotics Reports (2021) 2:189–200
https://doi.org/10.1007/s43154-021-00048-3

DEFENSE, MILITARY, AND SURVEILLANCE ROBOTICS (S FERRARI AND P ZHU, SECTION EDITORS)

Multi-Agent Systems for Search and Rescue Applications

Daniel S. Drew [1]

Accepted: 3 March 2021 / Published online: 27 March 2021
© The Author(s), under exclusive licence to Springer Nature Switzerland AG 2021

Abstract

Purpose of Review The goal of this review is to evaluate the current status of multi-robot systems in the context of search and rescue. This includes an investigation of their current use in the field, what major technical challenge areas currently preclude more widespread use, and which key topics will drive future development and adoption.

Recent Findings Work blending machine learning with classical control techniques is driving progress in perception-driven autonomy, decentralized multi-robot coordination, and human–robot interaction, among others. Ad hoc mesh networking has achieved reliability suitable for safety-critical applications and may be a partial solution for communication. New modular and multimodal platforms may overcome mobility limitations without significantly increasing cost.

Summary Multi-agent systems are not currently ready for deployment in search and rescue applications; however, progress is being made in a number of critical domains. As the field matures, research should focus on realistic evaluations of constituent technologies, and on confronting the challenges of simulation-to-reality transfer, algorithmic bias in autonomous agents that rely on machine learning, and novelty-versus-reliability incentive mismatch

Keywords Urban search and rescue robots · Disaster robotics · Multi-robot search and rescue · Swarm search and rescue · Multi-agent systems; Field robotics

Introduction

Over one and a half million people lost their lives between 2000 and 2014 from natural disasters, like wildfires and earthquakes, and man-made disasters, like nuclear meltdowns and other industrial accidents [1, 2]. With the world bracing for increased rates of catastrophic events like hurricanes and increasing global population density leading to higher potential fatalities [2], there is a pressing need for technology that can help with disaster recovery. Robots are envisioned as useful tools for almost every type of disaster. In the future, they may serve as proxies for humans that can venture to unsafe areas, supplements to enhance human sensory and manipulation abilities, or explorers in terrain that human responders cannot navigate. Following decades of advances in robotic platform development, robots have been deployed in disaster response since as early as 2001 [3••]. Individual robots, however, still face a number of challenges in the field that could be overcome by using them as part of a multi-robot system.

A multi-robot system consists of multiple simultaneously operating robotic agents which cooperate in some way in order to accomplish tasks. Figure 1 shows three examples of multi-robot systems developed for recent search and rescue competitions. A number of factors make these systems particularly attractive in the context of search and rescue. For example, disasters can encompass extremely large areas that are impossible for a single robot to effectively explore, redundancy can ensure robustness to individual robot failure, and tasks that would be too complicated for any one platform can be decomposed into subtasks performed by many. Beyond searching for victims in need of aid, response tasks like map generation and network infrastructure installation also benefit from having many robots working simultaneously. Parallelization-based approaches for first responders, like grid-based search and human chains, are already practiced;

This article is part of the Topical Collection on *Defense, Military, and Surveillance Robotics*

✉ Daniel S. Drew
dsdrew@stanford.edu

[1] Mechanical Engineering, Stanford University, 738 Guinda St, Palo Alto, CA 94301, USA

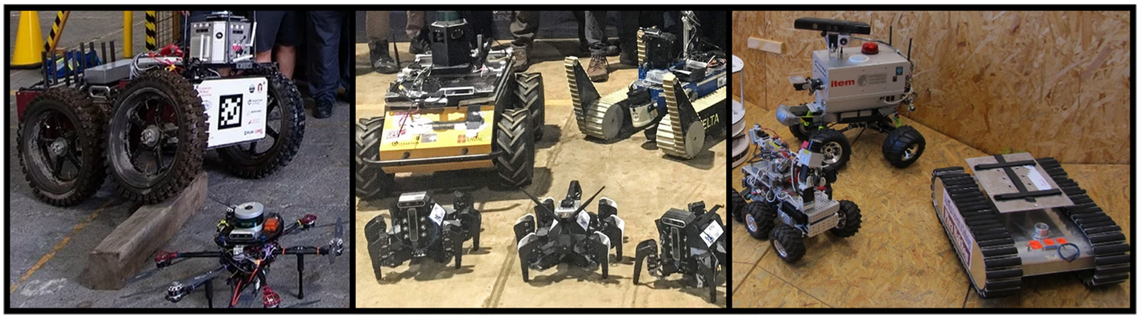


Fig. 1 Heterogeneous multi-robot systems designed for search and rescue. From left: The Explorer DARPA SubT challenge robots, CTU-CRAS-NORLAB DARPA SubT challenge robots [122], and Hector RoboCup Rescue League robots. (Reproduced with permission from www.subt-explorer.com, www.teamhector.de, and https://robotics.fel.cvut.cz/cras/)

using robots removes the need to wait for the recruitment of large numbers of volunteers.

Although academic work on multi-robot systems has progressed dramatically in recent years (Fig. 2), there is still a gap between current capabilities and those required for disaster response. Published field report data show that in the period from 2001 to present, there were at least 40 documented cases of robot-assisted disaster response efforts [3••, 4–8]. Of these documented cases, only four of them involved three or more robots deployed at once, and only two of those (both marine robots) involved a degree of autonomous operation. In no cases were robots explicitly cooperating to perform their tasks. While the promise of multi-robot systems in search and rescue is clear, there are still key challenges that must be overcome in order to close the gap between academic interest and their use in the field.

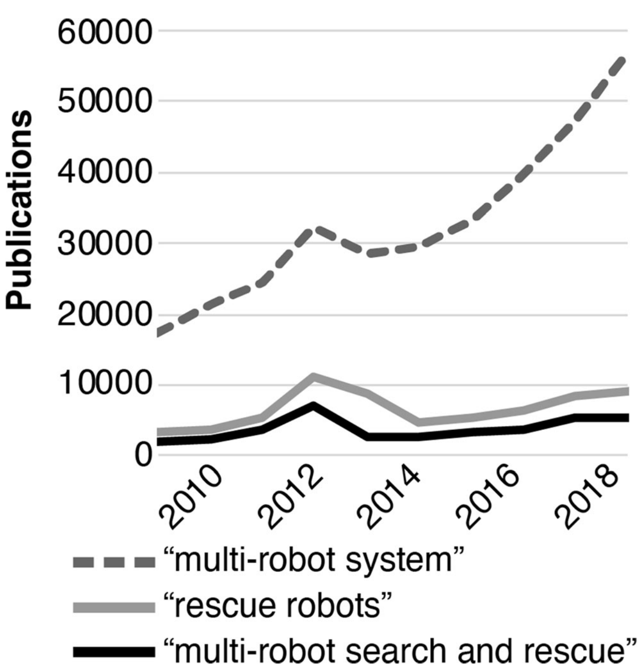


Fig. 2 Total number of publications per topic based on a keyword search of indexed metadata. Gathered using Dimensions software [123]

Note that although terminology differs in the literature, for the purposes of this review disaster robotics, search and rescue (SAR) robotics, and urban search and rescue (USAR) robotics are used interchangeably. Furthermore, this review is written generally in an attempt to provide information applicable to all forms of disaster response. The associated technical challenges can be narrowed dramatically depending on the exact response context; for example, in recovery from the Fukushima meltdown, communication infrastructure was existent and there was not significant time pressure related to victim localization, but platforms had to be specially designed to withstand the radiological environment. Erdelj et al. [9•] provide an example of how different disaster types drive different design constraints in the specific case of aerial robot fleets.

Technical Challenges for Multi-Robot Search and Rescue

This section provides an overview of some of the most critical technical challenges preventing multi-agent systems from being deployed for search and rescue. The challenge areas were chosen based on published surveys and interviews with practitioners [3••, 10] as well as conclusions from prior reviews on the topic [11••, 12, 13]. A significant portion of each challenge area relates to the notion of system *scalability*, defined as the implication on functionality as agent count increases. Three metrics can be used to broadly characterize the functionality of a multi-robot system: *reliability*, *autonomy*, and *mobility*. Figure 3 illustrates the relative importance of each of the identified challenge areas to these performance metrics, as determined qualitatively during review of the relevant literature. These determinations are made with a focus on the challenges inherent to MRS, such as scalability. For example, while improving the operator interface (i.e., an advancement in human–robot interaction) may improve mobility of a single platform during direct teleoperation, MRS-specific challenges in human–robot interaction (HRI), such as one-to-many control, are more directly relevant to autonomy and reliability. A graphical overview of this section and the contained subtopics is shown in Fig. 4.

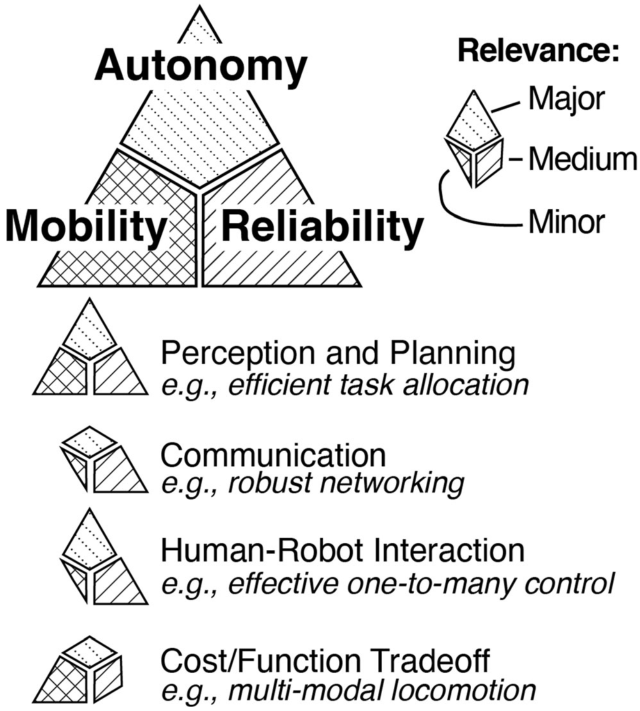


Fig. 3 Qualitative relevance of each of the discussed technical challenge areas to the multi-robot system (MRS) functionality metrics of autonomy, mobility, and reliability. For example, advances in Human–Robot Interaction (HRI) will be major contributors to improved autonomy and reliability of MRS for search and rescue. Note that this figure is intended to pair the relevance of new research advances to new improvements in functionality, not as a retrospective assessment

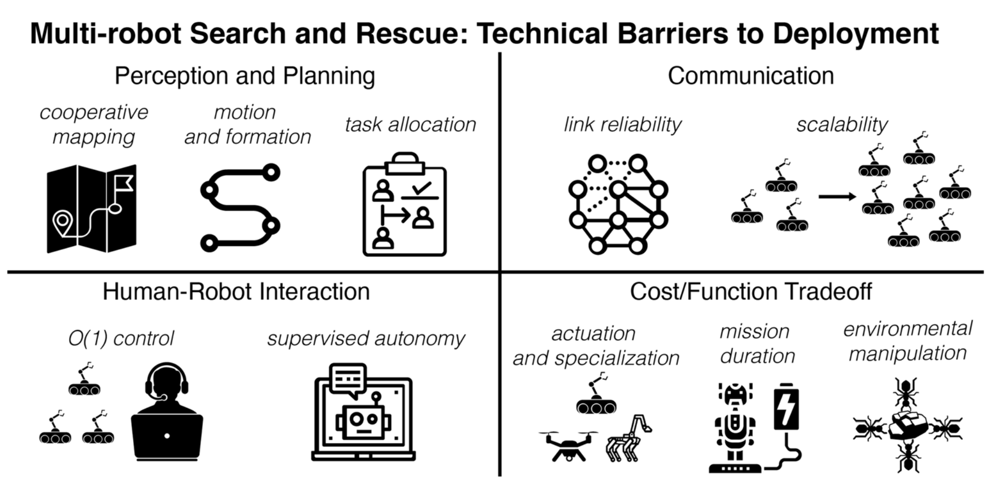
Perception and Planning

The abilities to reconstruct the world around them from incoming sensory data, navigate safely in the face of obstacles, and decide on the correct course and timing of actions are all vital aspects of robot operation. Multi-robot systems add on further challenges by demanding not only individual agent autonomy but also system-level requirements, like effective sharing of information and the ability to decide which constituent robots of the group should be assigned to perform individual tasks. The search and rescue context demands low failure-rate performance in some of the most challenging conditions possible for today's robots.

Often, one of the first tasks in disaster response is constructing an operation map for other first responders, making simultaneous localization and mapping (SLAM) a critical feature for search and rescue robots [3••]. Surveys of recent advances in SLAM [14•] and in multi-robot SLAM (or "cooperative mapping") [15] are available. Search and rescue is a particularly interesting application space for developing SLAM techniques because of inherent challenges with inter-robot communication and the unstructured, dynamic nature of the environments. Fully distributed multi-robot SLAM techniques, which do not assume full agent connectivity, may be a partial solution to the communication challenge [16]. Semantic segmentation-based SLAM shows promise for unstructured and ambiguous environments like those encountered in SAR [17]. Realistic hardware demonstrations for multi-robot search and rescue SLAM are bottlenecked by practical challenges like platform cost and the availability of large, safe testing environments. Although logistically challenging, development of a publicly accessible robot collection, for example, in the style of the Georgia Tech Robotarium [18], is a promising solution to the current lack of truly compelling (from the perspective of search and rescue) demonstrations.

Challenges associated with motion planning for autonomous robot navigation are highly specific to the usage environments and performance demands. Recent reviews of motion planning for mobile robots in general [19] and specifically in dynamic environments [20, 21] are available. In general, motion planning is relatively mature in highly structured environments like warehouses, but still a great challenge in many of the situations common to disaster areas like dynamic obstacles, complex geometries, and fluctuating or adverse environmental conditions like smoke. Perception-driven

Fig. 4 A graphical overview of the technical challenge areas related to the use of multi-robot systems for search and rescue applications, which corresponds to the subtopics discussed in more detail within the text



autonomy which can function in unstructured and dynamic environments is developing rapidly, with recent results demonstrating even aggressive maneuvering of a UAV using on-board computation [22, 23]. Multi-robot systems have the additional challenge of ensuring no robot-to-robot collisions occur during deployment. Formation control and collision-free trajectory planning is a topic with significant recent progress, as surveyed in [24]. Recent work on decentralized formation control using only visual information and on-board processing is promising, with hardware demonstrations of up to 12 quadrotors in low light conditions [25].

Efficient task allocation is a major challenge to ensuring the scalability of multi-robot systems. A recent general survey of different approaches to task allocation in multi-robot systems is given in [26•]. This challenge is compounded by factors such as the communication range limits, imperfect global state estimation, and control delay present in many search and rescue applications. The constraint of maintaining communication range during task performance is captured by the notion of cross-schedule dependencies, as described in recent comprehensive task-allocation taxonomies [27]. Approaches which explicitly take into account uncertainty in state estimation are likely to be important [28]. In addition, many of the robotic deployments for past disaster recovery efforts have been heterogeneous in nature, involving some combination of ground, air, and marine platforms. Task allocation for heterogeneous multi-robot systems that takes differing platform capabilities into account will be important as more autonomous operation is incorporated [29].

Communication

One of the major challenges associated with autonomous and semi-autonomous multi-agent systems is routing state and control data to and from the members. A related architectural decision for multi-robot control is between centralized, where a base station receives state information and then computes high level trajectories for individual agents, and decentralized, where robots make decisions internally using their own current view of the world and the other robots inside it. Both centralized and decentralized methods rely on communication of state information. Based on a formalism established in [30], methods of communication can be described as *explicit*, where messages are sent in direct peer-to-peer routed links, or *implicit*, where messages are mediated by modifications to or changes in the shared environment.

A major difficulty in using explicit communication methods for multi-robot systems is the tradeoff between scalability and bandwidth; agents must share the total network capacity, reducing each one's share as more are active [31]. Agents must, typically, time-multiplex their transmissions within some predefined slotting system in order to maintain reliability [32]. In addition, during disaster-related operations, the common issues with reliable wireless communication in areas lacking preexisting infrastructure such as multipath fading are exacerbated by domain-specific challenges, like interference from collapsed metal-rich structures, malfunctioning and/or damaged equipment, and large numbers of decentralized response efforts all relying on the same frequency bands. Path planning algorithms which respond to changes in communication performance in real time are a promising solution [33].

Ad hoc wireless mesh networking stacks are emerging that enable relatively robust communication to a base node using dynamically reconfigurable (e.g., as the robots move) topologies [34, 35]. Such implementations have been demonstrated in long-term real-world deployments with large numbers of static nodes, for example, in the ARHO project with almost 1000 networked sensors [36]. Taking advantage of frequency diversity in the network through a concept known as channel-hopping, where radio devices dynamically change which portion of the frequency spectrum they are communicating on based on network conditions, has been shown to improve reliability to levels that satisfy safety-critical applications [37]. There is still an inherent tradeoff between maximum individual agent data throughput and total agent count that sets constraints on the number of robots in the system given some minimum amount of information, or maximum latency, required for operation. There are few examples of actual deployments of mesh network enabled robots (one example is with a group of 10 UAVs [38]). Integrating open-source efforts to release full-stack Internet-of-Things packages based on this technology [39] with the robotic platforms is a promising path forward.

New methods to supplement radio-frequency communication should also be explored in order to both improve reliability through redundancy and complement existing functionality. Line of sight communication for fleets of autonomous UAVs has been demonstrated in wide ranging light conditions [40], but guarantees on sightlines are difficult to make due to the large nature of typical search and rescue environments and the presence of smoke and dust, which can reduce signal from visual, IR, and laser systems. Ultrasonic and acoustic [41, 42] communication and sensing for teams of robots has been demonstrated, but reliability has not been assessed in a realistic search and rescue environment and there exists no meta-study of acoustic conditions in disaster areas. In the case of autonomous underwater vehicles specifically, acoustic networking has been validated as a method to cooperatively navigate in the field without the need for resurfacing [43]. Sound source localization for search and rescue (e.g., for victim finding) using airborne microphone arrays is an area of current research [44, 45]; using the same acoustic sensing systems for robot colocalization could be an interesting area for future work.

Moving toward more decentralized control [46,47] is one way to enable multi-agent systems to operate cooperatively despite lacking high bandwidth communication links to base stations and to obviate some of the challenges associated with scaling to high agent counts. Machine learning–based approaches to derive communication requirements for robot teams is one way to reduce required inter-robot network bandwidth [48]. Implicit communication strategies can ensure information is still transferred between decentralized robots without the inherent scalability challenges of explicit methods. In a concept known as stigmergy, inspired by the communication strategies employed by social insects [49], robots modify their surrounding environment either through deployment of supplementary networking devices (e.g., RFID tags [50, 51] or 802.15.4 RF motes [35]) or by mechanical means (e.g., chemical spraying [52]). While current implementations are a far cry from the high levels of functionality exhibited by insects (e.g., using pheromones [53]) in terms of carrying capacity, signal diversity, and range, advances in millimeter and sub-millimeter wireless motes [54] could lead to more capability in the future. Rather than modifying the environment directly, other work focuses on using the implicit information communicated by the actions being undertaken by other robots, similar to the concept of human body language, in order to coordinate tasks without direct communication [55].

Human–Robot Interaction (HRI)

Challenges related to human–robot interaction are perceived by a majority of both practitioners and researchers as a major barrier to adoption of robots for search and rescue operations [10]. There are well-documented challenges related to teleoperation of ground, aerial, and marine robots in general [56] and in search and rescue environments specifically [57]. As a result, operators must be highly trained, and even then, failure due to operator error has occurred in both routine and critical disaster settings [58]. Best practices for future interface design of search and rescue and other field robots, as distilled from research and practitioner interviews, are listed in [59•]. Interaction design for multi-robot systems is even more challenging due to cognitive burden increasing with robot count, robots of disparate abilities being dispersed through disparate environments, and the high cost of failure making fully autonomous operation dangerous.

Control complexity in a multi-robot system can be defined in similar ways to computational complexity. For example, if a group of robots are operating completely independently, then the operator cognitive load is order $O(n)$ and total effort scales linearly with robot count. Given the challenges associated with 1:1 and even 2:1 teleoperation of robots in search and rescue scenarios, simultaneously increasing agent count, decreasing effort burden, and maintaining (or beginning to make) safety guarantees is both tremendously difficult and tremendously important. Research in the space of human–swarm interaction, as surveyed in [60], aims to move toward $O(1)$ effort for arbitrarily large groups of robots and has seen recent success, although typically only in simple, simulated environments and tasks. As multi-robot systems increase in agent count and swarm hardware platforms increase in capability these fields may truly converge, but in the meantime, practices uncovered by the swarm community should not be discounted by those who work using more "traditional" multi-agent platforms and numbers.

New schemes for human–robot interaction vary greatly depending on whether they are intended for proximal or remote use. While the latter is currently the most common in search and rescue, human–robot proximal teaming is of growing interest. In the case of proximal interactions, gesture-based cues have been explored for groups of up to 20 aerial [61] and 20 ground-based [62] robots, although not validated in the field. Recent work uses human-centered design practices to assess how these types of interaction modalities scale to larger agent count systems [63]. Remote interaction (i.e., outside audible or visual range) is largely mediated through electronic devices. While this topic has been explored for some time, with seminal work appearing as early as 2005 [64], documented challenges with effective control as agent count increases still exist [60]. To combat cognitive load, there has been a trend toward interfaces that offer the operator some form of future state prediction [65]. Interfaces that allow high-level task specification and therefore abstract out the specifics of planning may help simplify task allocation for robots of disparate abilities.

In the context of multi-robot systems, advances in HRI that will allow for more effective one-to-many operation are inseparable from advances in autonomy. Realistically, however, the high cost of failure (e.g., in victim identification) means that human-in-the-loop control is likely for the foreseeable future of disaster robotics. A research direction that explicitly connects the two is that of sliding, shared, or adjustable autonomy [66], where agents can transition on a scale from fully autonomous to teleoperated based on situational context. Such a strategy could allow human operators to aid in difficult navigation or identification tasks for multiple robots without incurring the full cognitive load burden of direct teleoperation. Leveraging learned models of human preferences (i.e., when in a given scenario they would most likely take over direct teleoperation of an agent) [67, 68] and learned models of when robots are likely to require intervention (e.g., by assessing incoming sensory data for statistical anomalies [69] or by incorporating human control expected utility into a learned policy [70]) in order to automate the sliding autonomy control handoff could further reduce operator training requirements and attention burden.

Balancing Cost and Functionality

There is an inherent tradeoff between price, functionality, and agent count for a multi-robot system. Given a static budget, the core effort is to balance the gains from parallelization (i.e., through the use of more robots) with the loss in individual platform functionality that eventually means they become unusable. The search and rescue domain places additional lower bounds on requisite mobility and independence for a platform.

There are fundamental mobility issues associated with ground robots that are affordable enough to be deployed in large numbers. For example, despite the relative maturity of robots using treads and wheels, they are still infrequently deployed in rescue environments due to challenges in guaranteeing that they will be able to navigate a priori unknown terrain with even state of the art locomotive capabilities [11••]. In part motivated by the need to overcome mobility challenges in smaller low-cost ground platforms, there has been a relatively recent trend toward development of modular robots [71, 72]. There are examples of modular robots built specifically for search and rescue [73] as well as with obstacle navigation in search and rescue as at least partial motivation [74]. Recent efforts towards perception-driven autonomy [75] for modular robot systems are encouraging, albeit in structured laboratory environments. Less dramatic platform changes, like adding alternate locomotion strategies (e.g., wheels for legged robots [76]) or driving down the cost of legged robots [77], may be important nearer-term solutions.

Improving usability of ground-based platforms is doubly important because for many applications there is a need to extend robotic mission lifetime. With current battery technology, decimeter-scale autonomy-capable UAVs have maximum flight durations of about 30 min in ideal cases. In the case of search and rescue, the average mission time for teleoperated UAVs is only about 10 min [5]. Smaller, less expensive drones which can be deployed in higher numbers have even shorter flight times. Further complicating this issue, multi-robot systems must allocate additional energy to inter-robot communication and formation control during routing, and typically have some overlap time during deployment that makes at least part of their operation time redundant instead of additive. In a disaster environment there may be no existing infrastructure to use for power scavenging, no safe space to wait for humans to reach the robot and recharge it, and no guarantee that a previously traversed path will remain static and therefore take the same amount of time on the return trip. Bimodal locomotion platforms [78, 79] which can switch between energy-efficient ground locomotion and flight when necessary will likely be important solutions. Explicitly taking into account energetic constraints during motion planning is a way to improve performance with no hardware modification [80]. Due to the heterogeneous nature of most projected search and rescue robot deployments, strategies for mobile ground-robot based charging of flying robot team members may be important [81].

Disaster areas may be filled with rubble and debris, making environmental manipulation useful for both mapping and victim identification. While traditional platforms have difficulty with autonomous manipulation tasks, multi-robot systems have the ability to work together for something known as cooperative manipulation or "cooperative transport." Demonstrations have typically relied on centralized approaches, based on high bandwidth connectivity, that are unsuitable for SAR. Recent work on fully decentralized methods for ground robot cooperative manipulation [82] is promising. Multi-robot motion planning algorithms which take into account laden payloads [83] will be necessary. Although perhaps the coordinated manipulation of rigid objects is more relevant to SAR, progress toward the more difficult case of deformable objects is surveyed in [84].

Translating Results from Simulation

There are known challenges with translation of results from simulation to hardware in robotics. Many of these challenges, for example, the difficulty in modeling the effect of adverse environmental conditions on sensor input, are especially significant in the context of search and rescue [85]. In the early 2000s, there was an effort within the RoboCup Rescue community to move toward large-scale physics-based simulations using the USARSim platform [86], which significantly improved simulation fidelity and in doing so helped guide research toward solving SAR-specific challenges. There has recently been a shift in RoboCup, however, toward using ROS and Gazebo [87] for simulation. Motivated by challenges in simulation-to-reality transfer in systems developed using tools like Gazebo, there is recent research building photorealistic simulation environments for robotics like Microsoft AirSim [88] and Facebook AI Habitat [89]. As those tools mature, search and rescue robotics researchers, and RoboCup specifically, should transition to them. The DARPA SubT Virtual simulation environment is a good example of a current program trying to bridge this gap [90]. Even the most realistic simulation environment cannot account for all possible circumstances in a highly dynamic space like search and rescue; recent work on uncertainty aware predictions for deep learning may make findings more translatable to situations outside the training data set [91]. Known challenges in translating HRI findings from simulation to real hardware can benefit from recent expert guidelines [92].

Toward Equitable Access to Life-Saving Robotic Technology

There already exists a documented discrepancy in access to life-saving technologies and in efficacy of response efforts as a result of regional and socioeconomic inequalities, both globally and more narrowly (e.g., within individual cities of the USA) [93–96]. In the near term, deployment of individual robotic and multi-robot systems for search and rescue is likely

Table 1 Relevant programs and competitions for multi-robot system (MRS) search and rescue (SAR)

Program/competitionProgram/ competition	Years active	Funding	MRS	SAR	Field test	Organization region
ERL Emergency [106]	2018–present			√	√	Europe
NSF NRI and NRI2.0 [124]	2013–present	Recurring	†	†		USA
ARCHE [108]	2018–present			√	√	Switzerland
DARPA SubT (Systems) [90]	2018–present	Prize*	•	√	√	USA
DARPA SubT (Virtual) [90]	2018–present	Prize*	•	√		USA
MBZIRC [105]	2017–present	Prize	√		√	UAE
ELROB [106]	2008–present				√	Europe
RoboCup Rescue (RRL) [117••]	2010–present		√	√	√	Europe
Rescue Simulation (RSL) [117••]	2010–present		√	√		Europe
Odyssey [115]	2018–2019	Prize		√	√	Russia
TRADR [111]	2014–2018	Recurring	√	√	√	Europe
ICARUS [112]	2012–2017	Recurring		√	√	Europe
ARGOS [104]	2013–2017	Recurring			√	Europe
SHERPA [113]	2013–2017	Recurring	√	√	√	Europe
DARIUS [114]	2012–2015	Recurring	√	√	√	Europe
DARPA Robotics Challenge [109]	2013–2015	Prize		√	√	USA
euRathlon [110]	2013–2015	Recurring	√	√	√	Europe
MAGIC [116]	2009–2010	Prize	√		√	USA, Australia
AAAI Robot Rescue [118]	2000–2007		•	√	√	USA

*Recurring funding also offered to a subset of teams. †Although not explicitly focused on MRS or SAR, at least five individual research awards made by this program (out of over 200) have been. • Not explicit focus, but multiple teams have some degree of collaboration between robots

to make these discrepancies even more pronounced due to the high capital and training investments required. Efforts to reduce overall equipment cost and the cost associated with operator training are therefore important not only as feats of engineering but as ones that serve a more equitable future.

Multi-agent systems will rely on individual agent autonomy and decision-making for effective use. The current trend is toward the use of machine learning (ML) algorithms for the majority of tasks related to vision and detection [97], and increasingly learning algorithms feed in to the ability of robots to manipulate and reason about task feasibility [98]. Despite rapid progress in these domains there exists a documented issue with algorithmic fairness in the ML community [99–101]. In the context of search and rescue, issues with non-White facial recognition inaccuracy could prevent victims from being identified by robots, and reward functions hand-tuned by researchers with implicit biases could lead robots to target their search patterns in ways that neglect historically disenfranchised communities. Perhaps search and rescue is a valuable framing of these topics, making it harder for researchers to think about failures as inconveniences and instead as, potentially, the difference between life and death.

There are also questions related to privacy and trust regarding the data collected during search and rescue operations, whether it is by government actors or by private contractors. These questions are made more difficult by the fact that traditional boundaries between public and private spaces can weaken during times of crisis either from a sense of urgency or from physical destruction of barriers [102, 103]. Debate surrounding proper censoring and anonymization of autonomously collected video and demographic data should be reexamined in this context, and researchers should carefully consider what information is strictly necessary for improving safety.

Aligning Research Efforts with Public Interest

Challenges, competitions, and other multi-group initiatives have historically been important for driving robotics research forward. Since the early 2000s, there have been a number of these programs focused specifically or tangentially on search and rescue robotics, including ARGOS [104], MBZIRC [105], ERL [106], ELROB [107], DARPA SubT [90], ARCHE [108], the DARPA Robotics Challenge [109], euRathlon [110], TRADR [111], ICARUS [112], SHERPA [113], DARIUS [114], Odyssey [115], and MAGIC [116]. The longest running and most directly relevant competition related to multi-agent search and rescue is the RoboCup Rescue League (RRL) [117••], the successor to the AAAI Robot Rescue competition [118]. A recent survey of rescue competitions can be found in [119•]. Table 1, a collection of recent robotics challenges and programs and their relevance to multi-robot search and rescue, illustrates a clear problem: there is not enough funding to push researchers toward this difficult topic in a focused way, especially within the USA (i.e., the majority of listed multi-robot search and rescue programs, and the majority of RRL teams, are from the European Union). While recent efforts like the DARPA SubT challenge are promising, it is focused solely on underground terrain and does not explicitly call for multi-robot systems. Given the high cost of both developing or acquiring multiple experimental hardware platforms and performing realistic field testing, more sources of ongoing, multi-year funding are necessary. Prize-only funding models will both unfairly handicap new and upcoming groups and likely reduce participation rates altogether.

Translating research from the laboratory (or competition) to the real world is difficult in any case. Search and rescue robots face additional difficulty with their uncertain route toward commercialization and the requirement of operating in some of the most technically challenging conditions possible, making research on this topic relatively high risk. Further, the gap in reliability between commercially available robots and a typical research-grade system means that penetration of any novel platform will be slow. Truly assessing reliability (e.g., to the point of failure) requires a significant investment of time and money. Unfortunately, there is fundamentally a misalignment of the goal structures between academics and practitioners, where high value is placed on novelty (perhaps exacerbated by the annual conference deadline structure) for the former while system reliability and robustness are the primary concerns for actual deployment [11••]. This is a structural challenge that will take concerted effort from funding agencies and publication venues to solve.

Conclusion

As the coordination algorithms, platform functionality, and interaction methodology improve for multi-robot systems, they will become increasingly viable for responding to disasters. There is currently encouraging research on every technical challenge front. Moving forward, proper alignment of stakeholder values with academic research directions and funding streams that focus on realistic, equitable technology integration will ensure that life-saving deployments happen as quickly as possible.

While this paper has focused on disaster early-response activities, true disaster response plans include preparatory, response, and recovery phases [3]. In the future, increasing levels of autonomy will be leveraged to expand the use of robotic assistance in the preparatory and recovery phases of disaster response, with specific use cases ranging from persistent infrastructure monitoring [120] to reconstruction of damaged property [121].

Acknowledgment This research was supported by an appointment to the Intelligence Community Postdoctoral Research Fellowship Program at Stanford University, administered by Oak Ridge Institute for Science and Education through an interagency agreement between the U.S. Department of Energy and the Office of the Director of National Intelligence.

Declarations

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

Conflict of Interest The author declares that he has no conflict of interest.

References

Papers of particular interest, published recently, have been highlighted as:
• Of importance
•• Of major importance

1. World Disasters Report. IFRC campaigns. 2015. http://ifrc-media.org/interactive/world-disasters-report-2015/. Accessed 8 Jul 2020.
2. World Disasters Report 2010 - Urban Risk - IFRC. https://www.ifrc.org/en/publications-and-reports/world-disasters-report/wdr2010/. Accessed 8 Jul 2020
3.•• Murphy RR, Tadokoro S, Kleiner A. Disaster Robotics. In: Siciliano B, Khatib O, editors. Springer Handb. Robot. Cham: Springer International Publishing; 2016. p. 1577–604. **This review collects and analyzes field reports over the past two decades and contains insights from some of the preeminent field roboticists working in this space.**
4. Kruijff-Korbayová I, Freda L, Gianni M, et al. Deployment of ground and aerial robots in earthquake-struck Amatrice in Italy (brief report). In: 2016 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR); 2016. p. 278–9.
5. Fernandes O, Murphy R, Adams J, Merrick D. Quantitative data analysis: CRASAR small unmanned aerial Systems at Hurricane Harvey. In: 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR); 2018. p. 1–6.
6. Whitman J, Zevallos N, Travers M, Choset H. Snake robot urban search after the 2017 Mexico City earthquake. In: 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR); 2018. p. 1–6.
7. Adams J, Hart L, McBride J, Merrick D, Murphy R. Use of small unmanned aerial Systems for Tactical Response during Kilauea volcano lower east rift zone event. In: 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR); 2018. p. 1–2.
8. Murphy RR, Duncan BA, Collins T, Kendrick J, Lohman P, Palmer T, et al. Use of a small unmanned aerial system for the SR-530 Mudslide Incident near Oso, Washington. J Field Robot. 2016;33:476–88.

9.• Erdelj M, Natalizio E, Chowdhury KR, Akyildiz IF. Help from the sky: leveraging UAVs for disaster management. IEEE Pervasive Comput. 2017;16:24–32 **A recent survey focused specifically on how fleets of UAVs can be used for disaster response, interesting in that it divides envisioned implementations based on both Disaster Stage (e.g., Preparedness, Response, and Recovery) and Type (e.g., geophysical, climatological).**

10. Murphy RR, Kleiner A. A community-driven roadmap for the adoption of safety security and rescue robots. In: 2013 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR); 2013. p. 1–5.

11.•• Delmerico J, Mintchev S, Giusti A, et al. The current state and future outlook of rescue robotics. J Field Robot. 2019;36:1171–91 **This review is broad but contains a well-sourced overview of topics pertaining to ground and aerial platforms for robotic search and rescue. It is authored by some of the preeminent academic researchers working in the fields of autonomy, control, and novel platforms.**

12. Williams A, Sebastian B, Ben-Tzvi P. Review and analysis of search, extraction, evacuation and medical field treatment robots. J Intell Robot Syst. 2019;96:401–18.

13. Liu Y, Nejat G. Robotic urban search and rescue: a survey from the control perspective. J Intell Robot Syst. 2013;72:147–65.

14.• Cadena C, Carlone L, Carrillo H, Latif Y, Scaramuzza D, Neira J, et al. Past, present, and future of simultaneous localization and mapping: toward the robust-perception age. IEEE Trans Robot. 2016;32:1309–32 **Simultaneous localization and mapping is one of the most critical topics for field robotics in general and for multi-robot search and rescue in particular. This is a recent overview of the topic and contains a number of useful references for state-of-the-art research.**

15. Zou D, Tan P, Yu W. Collaborative visual SLAM for multiple agents: a brief survey. Virtual Real Intell Hardw. 2019;1:461–82.

16. Lajoie P-Y, Ramtoula B, Chang Y, Carlone L, Beltrame G. DOOR-SLAM: Distributed, Online, and Outlier Resilient SLAM for Robotic Teams. IEEE Robot Autom Lett. 2020;5: 1656–63.

17. Bowman SL, Atanasov N, Daniilidis K, Pappas GJ. Probabilistic data association for semantic SLAM. In: 2017 IEEE International Conference on Robotics and Automation (ICRA); 2017. p. 1722–9.

18. Pickem D, Glotfelter P, Wang L, Mote M, Ames A, Feron E, et al. The Robotarium: a remotely accessible swarm robotics research testbed. In: 2017 IEEE International Conference on Robotics and Automation (ICRA); 2017. p. 1699–706.

19. Zafar MN, Mohanta JC. Methodology for path planning and optimization of mobile robots: a review. Procedia Comput Sci. 2018;133:141–52.

20. Mohanan MG, Salgoankar A. A survey of robotic motion planning in dynamic environments. Robot Auton Syst. 2018;100:171–85.

21. Jahanshahi H, Jafarzadeh M, Sari NN, Pham V-T, Huynh VV, Nguyen XQ. Robot motion planning in an unknown environment with danger space. Electronics. 2019;8:201.

22. Foehn P, Brescianini D, Kaufmann E, Cieslewski T, Gehrig M, Muglikar M, Scaramuzza D (2020) AlphaPilot: Autonomous Drone Racing. ArXiv200512813 Cs Eess

23. Manderson T, Wapnick S, Meger D, Dudek G (2020) Learning to drive off road on smooth terrain in unstructured environments using an on-board camera and sparse aerial images. ArXiv200404697 Cs

24. Liu Y, Bucknall R. A survey of formation control and motion planning of multiple unmanned vehicles. Robotica. 2018;36: 1019–47.

25. Weinstein A, Cho A, Loianno G, Kumar V. Visual inertial odometry swarm: an autonomous swarm of vision-based quadrotors. IEEE Robot Autom Lett. 2018;3:1801–7.

26.• Khamis A, Hussein A, Elmogy A. Multi-robot task allocation: a review of the state-of-the-art. In: Koubâa A, Martínez-de Dios JR, editors. Coop. Robots Sens. Netw. 2015. Cham: Springer International Publishing; 2015. p. 31–51. **Efficient task allocation in the face of uncertainty is a core challenge in multi-robot search and rescue. This is a recent overview of the topic and contains a number of useful references for state-of-the-art research.**

27. Korsah GA, Stentz A, Dias MB. A comprehensive taxonomy for multi-robot task allocation. Int J Robot Res. 2013;32:1495–512.

28. Choudhury S, Gupta JK, Kochenderfer MJ, Sadigh D, Bohg J (2020) Dynamic multi-robot task allocation under uncertainty and temporal constraints. ArXiv200513109 Cs

29. Pickem D, Glotfelter P, Wang L, Mote M, Ames A, Feron E, et al. The Robotarium: a remotely accessible swarm robotics research testbed. In: 2017 IEEE International Conference on Robotics and Automation (ICRA); 2017. p. 1699–706.

30. Farinelli A, Iocchi L, Nardi D. Multirobot systems: a classification focused on coordination. IEEE Trans Syst Man Cybern Part B Cybern. 2004;34:2015–28.

31. Ghena B, Adkins J, Shangguan L, Jamieson K, Levis P, Dutta P. Challenge: unlicensed LPWANs are not yet the path to ubiquitous connectivity. In: 25th Annu. Int. Conf. Mob. Comput. Netw. Los Cabos Mexico: ACM; 2019. p. 1–12.

32. Lauri M, Heinänen E, Frintrop S. Multi-robot active information gathering with periodic communication. In: 2017 IEEE International Conference on Robotics and Automation (ICRA); 2017. p. 851–6.

33. Varadharajan VS, St-Onge D, Adams B, Beltrame G. Swarm relays: distributed self-healing ground-and-air connectivity chains. IEEE Robot Autom Lett. 2020;5:5347–54.

34. Sánchez-García J, García-Campos JM, Arzamendia M, Reina DG, Toral SL, Gregor D. A survey on unmanned aerial and aquatic vehicle multi-hop networks: wireless communications, evaluation tools and applications. Comput Commun. 2018;119:43–65.

35. Drew DS, Kilberg B, Pister KSJ. Future mesh-networked pico air vehicles. In: 2017 International Conference on Unmanned Aircraft Systems (ICUAS); 2017. p. 1075–82.

36. Zhang Z, Glaser S, Watteyne T, Malek S. Long-term monitoring of the Sierra Nevada snowpack using wireless sensor networks. IEEE Internet Things J. 2020:1–1.

37. Dujovne D, Watteyne T, Vilajosana X, Thubert P. 6TiSCH: deterministic IP-enabled industrial internet (of things). IEEE Commun Mag. 2014;52:36–41.

38. Vásárhelyi G, Virágh C, Somorjai G, Tarcai N, Szörenyi T, Nepusz T, et al. Outdoor flocking and formation flight with autonomous aerial robots. In: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2014. p. 3866–73.

39. Chang T, Tuset-Peiro P, Vilajosana X, Watteyne T. OpenWSN OpenMote: Demo'ing a complete ecosystem for the industrial internet of things. In: 2016 13th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON); 2016. p. 1–3.

40. Walter V, Saska M, Franchi A. Fast mutual relative localization of UAVs using ultraviolet LED markers. In: 2018 Int. Conf. Unmanned Aircr. Syst: ICUAS; 2018. p. 1217–26.

41. Rivard F, Bisson J, Michaud F, Letourneau D. Ultrasonic relative positioning for multi-robot systems. In: 2008 IEEE International Conference on Robotics and Automation (ICRA); 2008. p. 323–8.

42. Kapoor R, Ramasamy S, Gardi A, Schyndel RV, Sabatini R. Acoustic sensors for air and surface navigation applications. Sensors. 2018;18:499.

43. Allotta B, Caiti A, Costanzi R, Di Corato F, Fenucci D, Monni N, et al. Cooperative navigation of AUVs via acoustic communication networking: field experience with the Typhoon vehicles. Auton Robot. 2016;40:1229–44.
44. Hoshiba K, Washizaki K, Wakabayashi M, Ishiki T, Kumon M, Bando Y, et al. Design of UAV-embedded microphone array system for sound source localization in outdoor environments. Sensors. 2017;17:2535.
45. Nakadai K, Kumon M, Okuno HG, et al. Development of microphone-array-embedded UAV for search and rescue task. In: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2017. p. 5985–90.
46. Ayanian N, Kumar V. Decentralized feedback controllers for multiagent teams in environments with obstacles. IEEE Trans Robot. 2010;26:878–87.
47. Michaud F, Lepage P, Frenette P, Letourneau D, Gaubert N. Coordinated maneuvering of automated vehicles in platoons. IEEE Trans Intell Transp Syst. 2006;7:437–47.
48. Paulos J, Chen SW, Shishika D, Kumar V. Decentralization of multiagent policies by learning what to communicate. In: 2019 International Conference on Robotics and Automation (ICRA); 2019. p. 7990–6.
49. Dorigo M, Bonabeau E, Theraulaz G. Ant algorithms and stigmergy. Futur Gener Comput Syst. 2000;16:851–71.
50. Johansson R, Saffiotti A. Navigating by stigmergy: a realization on an RFID floor for minimalistic robots. In: 2009 IEEE International Conference on Robotics and Automation (ICRA); 2009. p. 245–52.
51. Ziparo VA, Kleiner A, Nebel B, Nardi D. RFID-based exploration for large robot teams. In: Proceedings 2007 IEEE International Conference on Robotics and Automation (ICRA); 2007. p. 4606–13.
52. Fujisawa R, Imamura H, Hashimoto T, Matsuno F. Communication using pheromone field for multiple robots. In: 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2008. p. 1391–6.
53. Hölldobler B, Wilson EO. The ants: Harvard University Press; 1990.
54. Chang T, Watteyne T, Wheeler B, et al. 6TiSCH on SCμM: running a synchronized protocol stack without crystals. Sensors. 2020;20:1912.
55. Losey DP, Li M, Bohg J, Sadigh D. Learning from my partner's actions: roles in decentralized robot teams. In: Conference on robot learning; 2020. p. 752–65.
56. Human–robot interaction: status and challenges - Thomas B. Sheridan, 2016. https://journals-sagepub-com.stanford.idm.oclc.org/doi/full/10.1177/0018720816644364. Accessed 17 Jul 2020
57. Murphy RR, Burke JL. Up from the rubble: lessons learned about HRI from search and rescue. Proc Hum Factors Ergon Soc Annu Meet. 2005;49:437–41.
58. Murphy RR, Kravitz J, Stover SL, Shoureshi R. Mobile robots in mine rescue and recovery. IEEE Robot Autom Mag. 2009;16:91–103.
59.• Murphy RR, Tadokoro S. User interfaces for human–robot interaction in field robotics. In: Tadokoro S, editor. Disaster Robot. Results ImPACT Tough Robot. Chall. Cham: Springer International Publishing; 2019. p. 507–28. **A set of guidelines distilled from field reports, references, and expert interviews for designing HRI interfaces, with a focus on real deployment constraints. Although the interfaces are not specifically for multi-robot systems, many of the guidelines are still relevant.**
60. Kolling A, Walker P, Chakraborty N, Sycara K, Lewis M. Human interaction with robot swarms: a survey. IEEE Trans Hum-Mach Syst. 2016;46:9–26.
61. Nagi J, Giusti A, Gambardella LM, Di Caro GA. Human-swarm interaction using spatial gestures. In: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2014. p. 3834–41.
62. Alonso-Mora J, Haegeli Lohaus S, Leemann P, Siegwart R, Beardsley P. Gesture based human - multi-robot swarm interaction and its application to an interactive display. In: 2015 IEEE International Conference on Robotics and Automation (ICRA); 2015. p. 5948–53.
63. Kim LH, Drew DS, Domova V, Follmer S. User-defined swarm robot control. In: Proc. 2020 CHI Conf. Hum. Factors Comput. Syst. Honolulu, HI, USA: Association for Computing Machinery; 2020. p. 1–13.
64. McLurkin J, Smith J, Frankel J, Sotkowitz D, Blau D, Schmidt B. Speaking swarmish: human-robot interface design for large swarms of autonomous mobile robots. In AAAI spring symposium: to boldly go where no human-robot team has gone before 2006 Mar 28 (Vol. 72).
65. Chen JYC, Barnes MJ, Harper-Sciarini M. Supervisory control of multiple robots: human-performance issues and user-interface design. IEEE Trans Syst Man Cybern Part C Appl Rev. 2011;41:435–54.
66. Sellner B, Heger FW, Hiatt LM, Simmons R, Singh S. Coordinated multiagent teams and sliding autonomy for large-scale assembly. Proc IEEE. 2006;94:1425–44.
67. Swamy G, Reddy S, Levine S, Dragan AD (2020) Scaled autonomy: enabling human operators to control robot fleets. ArXiv191002910 Cs Stat
68. Xu A, Dudek G. Towards modeling real-time trust in asymmetric human–robot collaborations. In: Inaba M, Corke P, editors. Robot. Res. 16th Int. Symp. ISRR. Cham: Springer International Publishing; 2016. p. 113–29.
69. Wu H, Guan Y, Rojas J. A latent state-based multimodal execution monitor with anomaly detection and classification for robot introspection. Appl Sci. 2019;9:1072.
70. Liu Y, Nejat G. Multirobot cooperative learning for semiautonomous control in urban search and rescue applications. J Field Robot. 2016;33:512–36.
71. Brunete A, Ranganath A, Segovia S, de Frutos JP, Hernando M, Gambao E. Current trends in reconfigurable modular robots design. Int J Adv Robot Syst. 2017;14:1729881417710457.
72. Seo J, Paik J, Yim M. Modular reconfigurable robotics. Annu Rev Control Robot Auton Syst. 2019;2:63–88.
73. Pfotzer L, Ruehl S, Heppner G, Roennau A, Dillmann R. KAIRO 3: a modular reconfigurable robot for search and rescue field missions. In: 2014 IEEE International Conference on Robotics and Biomimetics (ROBIO 2014); 2014. p. 205–10.
74. Mahkam N, Bakir A, Özcan O. Miniature modular legged robot with compliant backbones. IEEE Robot Autom Lett. 2020;5:3923–30.
75. Daudelin J, Jing G, Tosun T, Yim M, Kress-Gazit H, Campbell M. An integrated system for perception-driven autonomy with modular robots. Sci Robot. 2018;3:eaat4983.
76. Medeiros VS, Jelavic E, Bjelonic M, Siegwart R, Meggiolaro MA, Hutter M. Trajectory optimization for wheeled-legged quadrupedal robots driving in challenging terrain. IEEE Robot Autom Lett. 2020;5:4172–9.
77. Grimminger F, Meduri A, Khadiv M, et al. An open torque-controlled modular robot architecture for legged locomotion research. IEEE Robot Autom Lett. 2020;5:3650–7.
78. Mulgaonkar Y, Araki B, Koh J, Guerrero-Bonilla L, Aukes DM, Makineni A, et al. The flying monkey: a mesoscale robot that can run, fly, and grasp. In: 2016 IEEE International Conference on Robotics and Automation (ICRA); 2016. p. 4672–9.
79. Pope MT, Kimes CW, Jiang H, Hawkes EW, Estrada MA, Kerst CF, et al. A multimodal robot for perching and climbing on vertical outdoor surfaces. IEEE Trans Robot. 2017;33:38–48.

80. Karydis K, Kumar V. Energetics in robotic flight at small scales. Interface Focus. 2017;7:20160088.
81. Mathew N, Smith SL, Waslander SL. Multirobot rendezvous planning for recharging in persistent tasks. IEEE Trans Robot. 2015;31:128–42.
82. Culbertson P, Slotine J-JE, Schwager M (2020) Decentralized adaptive control for collaborative manipulation of rigid bodies. ArXiv200503153 Cs
83. Tang S, Sreenath K, Kumar V. Multi-robot trajectory generation for an aerial payload transport system. In: Amato NM, Hager G, Thomas S, Torres-Torriti M, editors. Robot. Res. Cham: Springer International Publishing; 2020. p. 1055–71.
84. Herguedas R, López-Nicolás G, Aragüés R, Sagüés C. Survey on multi-robot manipulation of deformable objects. In: 2019 24th IEEE Int. Conf. Emerg. Technol. Fact. Autom: ETFA; 2019. p. 977–84.
85. Carpin S, Lewis M, Wang J, Balakirsky S, Scrapper C. Bridging the gap between simulation and reality in urban search and rescue. In: Lakemeyer G, Sklar E, Sorrenti DG, Takahashi T, editors. RoboCup 2006 Robot Soccer World Cup X. Berlin, Heidelberg: Springer; 2007. p. 1–12.
86. Carpin S, Lewis M, Wang J, Balakirsky S, Scrapper C. USARSim: a robot simulator for research and education. In: Proc. 2007 IEEE Int. Conf. Robot. Autom; 2007. p. 1400–5.
87. Koenig N, Howard A. Design and use paradigms for gazebo, an open-source multi-robot simulator. In: 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2004. p. 2149–54.
88. Shah S, Dey D, Lovett C, Kapoor A. AirSim: high-fidelity visual and physical simulation for autonomous vehicles. In: Hutter M, Siegwart R, editors. Field Serv. Robot. Cham: Springer International Publishing; 2018. p. 621–35.
89. Savva M, Kadian A, Maksymets O, et al. Habitat: a platform for embodied AI research. In: Proceedings of the IEEE/CVF International Conference on Computer Vision; 2019. p. 9339–47.
90. DARPA Subterranean (SubT) Challenge. https://www.darpa.mil/program/darpa-subterranean-challenge. Accessed 7 Jul 2020.
91. McAllister R, Kahn G, Clune J, Levine S. Robustness to out-of-distribution inputs via task-aware generative uncertainty. In: 2019 International Conference on Robotics and Automation (ICRA); 2019. p. 2083–9.
92. Dole L, Ju W. Face and ecological validity in simulations: lessons from search-and-rescue HRI. In: Proc. 2019 CHI Conf. Hum. Factors Comput. Syst. Glasgow, Scotland UK: Association for Computing Machinery; 2019. p. 1–8.
93. Finch C, Emrich CT, Cutter SL. Disaster disparities and differential recovery in New Orleans. Popul Environ. 2010;31:179–202.
94. Davis JR, Wilson S, Brock-Martin A, Glover S, Svendsen ER. The impact of disasters on populations with health and health care disparities. Disaster Med Public Health Prep. 2010;4:30–8.
95. Rufat S, Tate E, Burton CG, Maroof AS. Social vulnerability to floods: review of case studies and implications for measurement. Int J Disaster Risk Reduct. 2015;14:470–86.
96. Black R, Arnell NW, Adger WN, Thomas D, Geddes A. Migration, immobility and displacement outcomes following extreme events. Environ Sci Policy. 2013;27:S32–43.
97. Voulodimos A, Doulamis N, Doulamis A, Protopapadakis E. Deep learning for computer vision: a brief review. Comput Intell Neurosci. 2018;2018:e7068349.
98. Niroui F, Zhang K, Kashino Z, Nejat G. Deep reinforcement learning robot for search and rescue applications: exploration in unknown cluttered environments. IEEE Robot Autom Lett. 2019;4:610–7.
99. Rajkomar A, Hardt M, Howell MD, Corrado G, Chin MH. Ensuring fairness in machine learning to advance health equity. Ann Intern Med. 2018;169:866–72.
100. Garcia M. Racist in the machine: the disturbing implications of algorithmic bias. World Policy J. 2016;33:111–7.
101. Buolamwini J, Gebru T. Gender shades: intersectional accuracy disparities in commercial gender classification. In: Conference on fairness, accountability and transparency; 2018. p. 77–91.
102. Finn RL, Wright D. Unmanned aircraft systems: surveillance, ethics and privacy in civil applications. Comput Law Secur Rev. 2012;28:184–94.
103. Hayes P, Kelly S. Distributed morality, privacy, and social media in natural disaster response. Technol Soc. 2018;54:155–67.
104. ARGOS - Autonomous robot for gas and oil sites challenge. http://www.argos-challenge.com/en. Accessed 7 Jul 2020.
105. MBZIRC - The Mohamed Bin Zayed International Robotics Challenge. https://www.mbzirc.com/challenge/2020. Accessed 7 Jul 2020.
106. European Robotics League - Emergency Robots. https://www.eu-robotics.net/robotics_league/erl-emergency/about/index.html. Accessed 7 Jul 2020.
107. ELROB - The European Land-Robot Trial | ELROB.org. https://www.elrob.org/. Accessed 7 Jul 2020.
108. ARCHE – Advanced Robotics Capabilities for Hazardous Environments. http://arche.website/en/home/. Accessed 7 Jul 2020.
109. Krotkov E, Hackett D, Jackel L, Perschbacher M, Pippine J, Strauss J, et al. The DARPA Robotics Challenge Finals: results and perspectives. J Field Robot. 2017;34:229–40.
110. Winfield AFT, Franco MP, Brueggemann B, et al. euRathlon 2015: a multi-domain multi-robot grand challenge for search and rescue robots. In: Alboul L, Damian D, Aitken JM, editors. Auton. Robot. Syst. Cham: Springer International Publishing; 2016. p. 351–63.
111. Kruijff-Korbayová I, Colas F, Gianni M, Pirri F, de Greeff J, Hindriks K, Neerincx M, Ögren P, Svoboda T, Worst R (2015) TRADR Project: long-term human–robot teaming for robot assisted disaster response. KI - Künstl Intell 29:193–201
112. De Cubber G, Doroftei D, Serrano D, Chintamani K, Sabino R, Ourevitch S. The EU-ICARUS project: developing assistive robotic tools for search and rescue operations. In: 2013 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR); 2013. p. 1–4.
113. Marconi L, Melchiorri C, Beetz M, et al. The SHERPA project: smart collaboration between humans and ground-aerial robots for improving rescuing activities in alpine environments. In: 2012 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR); 2012. p. 1–4.
114. Chrobocinski P, Makri E, Zotos N, Stergiopoulos C, Bogdos G. DARIUS project: deployable SAR integrated chain with unmanned systems. In: 2012 International Conference on Telecommunications and Multimedia (TEMU); 2012. p. 220–6.
115. IN SEARCH OF A MAN. http://odyssey.community/. Accessed 28 Jul 2020.
116. Olson E, Strom J, Morton R, Richardson A, Ranganathan P, Goeddel R, et al. Progress toward multi-robot reconnaissance and the MAGIC 2010 competition. Journal of Field Robotics. 2012;29:762–92.
117.•• Sheh R, Schwertfeger S, Visser A. 16 years of RoboCup Rescue. KI - Künstl Intell. 2016. https://doi.org/10.1007/s13218-016-0444-x **RoboCup Rescue League is the most directly relevant competition related to multi-robot systems for search and rescue. This review walks through the history of the competition, advances in the field, and notable findings of many of the participating teams.**
118. Casper J, Yanco H. AAAI/RoboCup-2001 Robot Rescue. AIMag. 2002;23:43–3.
119.• Shimizu M, Takahashi T. Survey of rescue competitions and proposal of new standard task from ordinary tasks. In: Holz D, Genter

K, Saad M, von Stryk O, editors. RoboCup 2018 Robot World Cup XXII. Cham: Springer International Publishing; 2019. p. 311–23. **Challenges and competitions have historically been important drivers of robotics research both broadly and more specifically in the context of disaster response robots. This survey details a number of competitions over the past two decades with a focus on their respective evaluation metrics.**

120. Asghar AB, Smith SL, Sundaram S. Multi-robot routing for persistent monitoring with latency constraints. In: 2019 American Control Conference (ACC); 2019. p. 2620–5.
121. A review of collective robotic construction | Science Robotics. https://robotics-sciencemag-org.stanford.idm.oclc.org/content/4/28/eaau8479.abstract. Accessed 21 Jul 2020.
122. Rouček T, Pecka M, Čížek P, et al. DARPA Subterranean Challenge: Multi-robotic Exploration of Underground Environments. In: Mazal J, Fagiolini A, Vasik P, editors. Model. Simul. Auton. Syst. Cham: Springer International Publishing; 2020. p. 274–90.
123. (2018) Dimensions. Digital Science, https://app.dimensions.ai
124. National Robotics Initiative 2.0: Ubiquitous Collaborative Robots | NSF - National Science Foundation. https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=503641. Accessed 29 Jul 2020.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.