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Collaborative Multi-Robot Search and Rescue: Planning, Coordination, Perception, and Active Vision

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ABSTRACT Search and rescue (SAR) operations can take significant advantage from supporting autonomous or teleoperated robots and multi-robot systems. These can aid in mapping and situational assessment, monitoring and surveillance, establishing communication networks, or searching for victims. This paper provides a review of multi-robot systems supporting SAR operations, with system-level considerations and focusing on the algorithmic perspectives for multi-robot coordination and perception. This is, to the best of our knowledge, the first survey paper to cover (i) heterogeneous SAR robots in different environments, (ii) active perception in multi-robot systems, while (iii) giving two complementary points of view from the multi-agent perception and control perspectives. We also discuss the most significant open research questions: shared autonomy, sim-to-real transferability of existing methods, awareness of victims' conditions, coordination and interoperability in heterogeneous multi-robot systems, and active perception. The different topics in the survey are put in the context of the different challenges and constraints that various types of robots (ground, aerial, surface, or underwater) encounter in different SAR environments (maritime, urban, wilderness, or other post-disaster scenarios). The objective of this survey is to serve as an entry point to the various aspects of multi-robot SAR systems to researchers in both the machine learning and control fields by giving a global overview of the main approaches being taken in the SAR robotics area.

INDEX TERMS Robotics, search and rescue (SAR), multi-robot systems (MRS), machine learning (ML), deep learning (DL), active perception, active vision, multi-agent perception, autonomous robots.

I. INTRODUCTION

Autonomous or teleoperated robots have been playing increasingly important roles in civil applications in recent years. Across the different civil domains where robots can support human operators, one of the areas where they can have more impact is in search and rescue (SAR) operations. In particular, multi-robot systems have the potential to significantly improve the efficiency of SAR personnel with faster response time [1], [2], support in hazardous environments [3]–[5], or providing real-time mapping and monitoring of the area where an incident has occurred [6], [7], among other possibilities. This paper presents a literature review of multi-robot systems (MRS) for SAR operations with a focus on coordination and perception algorithms and, specifically, how these two perspectives can be bridged through different active perception approaches. This algorithmic view of MRS for SAR is preceded in the paper by a system perspective of robotic SAR systems and their operational environments, some of which are illustrated in Fig. 1. The important abbreviations utilized throughout the paper are listed in Table 1.

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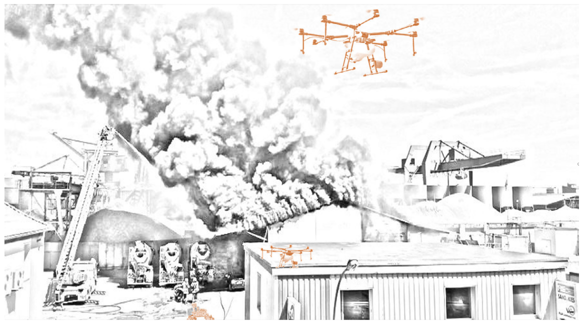
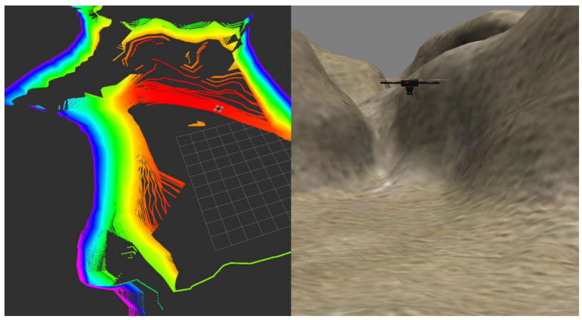
TABLE 1. List of important abbreviations used throughout the paper in alphabetical order.

Abbreviation	Definition
AT	Avalanche Transmitter
CNN	Convolutional Neural Network
CSAT	Cooperative Search, Acquisition and Tracking
CT	Cooperative Tracking
DL	Deep Learning
DRL	Deep Reinforcement Learning
EKF	Extended Kalman Filter
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IPP	Informative Path Planning
MANET	Mobile Ad-hoc Network
ML	Machine Learning
MPC	Model Predictive Control
MRS	Multi-Robot System
NP	Nondeterministic Polynomial Time
RGB-D	RGB + Depth
RL	Reinforcement Learning
ROS	Robot Operating System
RSSI	Received Signal Strength Indicator
SAR	Search and Recue
SLAM	Simultaneous Localization and Mapping
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
USAR	Urban Search and Rescue
USV	Unmanned Surface Vehicle
UUV	Unmanned Underwater Vehicle
UWB	Ultra-Wideband
WiSAR	Wilderness Search and Rescue

(a) Conceptual illustration of maritime search and rescue, where UAVs can replace or support helicopters.



(b) Illustration of urban search and rescue with UAVs and UGVs.



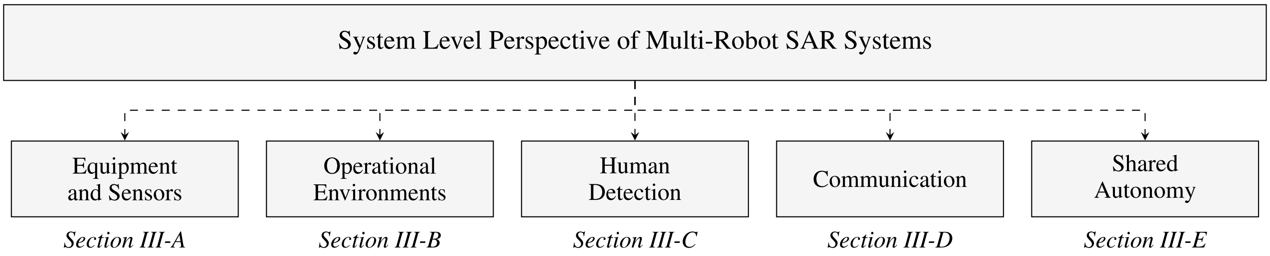
(c) Gazebo environment with hector quadrotor model and Rviz visualization tool. The simulator and robot were utilized in the RoboCup2019 Rescue Virtual Robot League.

(d) Illustration of the simulation environment for the DARPA SubT Virtual Challenge with two USVs and two UAVs.

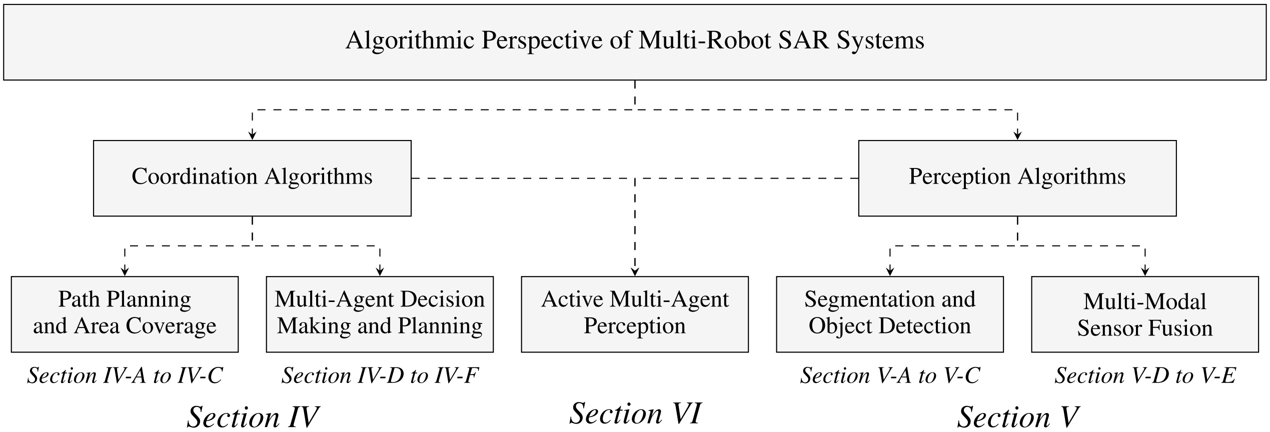
FIGURE 1. Conceptual and simulated SAR scenarios (maritime, urban, wilderness, underground).

The literature contains multiple survey papers that review robotics for SAR operations. Multi-UAV systems for civil applications (where SAR applications are a subset) are reviewed in [8] from the point of view of communication. A classification of technological trends and sensing modalities in UAVs for civil applications is available in [9]. Focusing on SAR robotics, UAVs for SAR operations are reviewed in [10], with a classification in terms of (i) sensing, (ii) system-level definitions, and (iii) operational environments. A study of MRS for SAR operations in [11] focuses on task allocation algorithms, communication modalities, and human-robot interaction for both homogeneous and heterogeneous multi-robot systems. While autonomous robots are being increasingly adopted for SAR missions, current levels of autonomy and safety of robotic systems only allow for full autonomy in the *search* part, but not for *rescue*, where human operators need to intervene [12]. In general, the literature on multi-robot SAR operations with some degree of autonomy is rather sparse, with most results being based on simulations or simplified scenarios [13].

The main objective of this survey is to provide a comprehensive introduction to multi-robot SAR systems from two complimentary perspectives: (i) control and coordination algorithms, and (ii) deep learning models for online perception. This review thus aims at providing an entry point to researchers from either of the two fields looking for a global view at MRS design for SAR operations. To that end, the paper starts with an overview of the most significant projects and competitions in the field, together with a system-level perspective (Fig. 2a. The survey is, in turn, closed with an introduction to multi-robot active perception, as the key piece to bridge control and perception design (Fig. 2b). Finally, we discuss the most important research directions and open challenges giving insight into key aspects in MRS design for



(a) Aspects of multi-robot SAR systems discussed in Section III of this paper.



(b) Division of multi-robot SAR systems into separate components from an algorithmic point of view. Control, planning and coordination algorithms are described in Section IV, while Section V reviews perception algorithms from a machine learning perspective. Section VI then puts these two views together by reviewing the works in single and multi-agent active perception.

FIGURE 2. Summary of the different aspects of multi-robot SAR systems considered in this survey, where we have separated (a) system-level perspective, and (b) planning and perception algorithmic perspective.

RAS operations, including shared autonomy, human condition awareness, multi-robot active perception, and challenges in heterogeneous MRS. This is, to the best of our knowledge, the first survey to cover simultaneously both coordination and control algorithms, and machine-learning-based perception, and the first one to review active perception approaches in MRS for SAR operations.

The remainder of this paper is organized as follows: Section II describes some of the most relevant projects in SAR robotics, with an emphasis on those considering multi-robot systems. Some of the most important competitions in SAR robotics are also presented in this section. In Section III, we present a system view on SAR robotic systems, describing the different types of robots being utilized, particularities of SAR environments, and different aspects for multi-robot SAR including communication and shared autonomy. Section IV follows with the description of the main algorithms in multi-agent planning and multi-robot coordination that can be applied to SAR scenarios. In Section V, we focus on machine vision and multi-agent perception from a deep learning perspective. Then, Section VI goes through the concept of active vision and delves into the integration of both coordination and planning algorithms with robotic vision towards active perception algorithms where the latter provides additional feedback to the control loops of the former. In Section VII, we discuss open research questions in the field of autonomous heterogeneous multi-robot systems for SAR operations, outlining the main directions that current research is being directed to. Finally, Section VIII concludes this work.

II. INTERNATIONAL PROJECTS AND COMPETITIONS

Over the past two decades, multiple international projects have been devoted to SAR robotics, often with the aim of working towards multi-robot solutions and the development of multi-modal sensor fusion algorithms. In this section, our objective is to give a general idea of the main specific objectives that different projects have had, which in turns gives an idea of the evolution of the technology and the current possibilities. We thus review the most relevant international projects and international competitions in SAR robotics, which are listed in Table 2. Some of the projects focus in the development of complex robotic systems that can be remotely controlled [14]. However, the majority of the projects consider multi-robot systems [15]–[18], and over half of the projects consider collaborative heterogeneous robots. In Table 2, we have described these projects from a system-level point of view, without considering the degree of autonomy or the control and perception algorithms. These latter two aspects are described in Sections III through VI, where not only these projects but also other relevant works are put into a more appropriate context.

TABLE 2. Selection of international projects and competitions in SAR robotics. We describe the utilization of different types of robots (UAV, USV, UGV), whether heterogeneous robots are employed, where the data is processed, and the characterization of networking and control strategies. The latter two aspects are only classified from a topological point of view in this table: centralized/predefined versus mesh/ad-hoc networks, and centralized versus distributed control. The application scenarios refer to either the specific objective of the project, or the scenarios utilized for testing. In the competitions section, each parameter defines the possibilities but not necessarily the characterization for all systems participating the challenges.

		Description	Multi-robot system	Auton. UGV	Auton. USV	Auton. UAV	Multi-UAV system	Heterogeneous robots	Sensor Data Processing	Ad-Hoc Network	Distributed control	Scenario
International Projects in SAR Robotics	**COMETS** (2002-2005)	Real-time coordination and control of multiple heterogeneous UAVs.	✓	✓	-	✓	✓	3xUAVs Heli+Airship	Offboard	-	-	Forest fire
	PeLoTe (2002-2005)	building presence through localization for hybrid human-robot telematic teams.	✓	✓	-	-	-	2xUGVs	✓	-	✓	Firefighting (+others)
	MEXT.DDT (2002-2007)	Aero, on-rubble/underground, and in-rubble robots for urban earthquakes.	✓	✓	-	✓	✓	UAVs+UGVs	✓	✓	-	Earthquake
	Guardians (2006-2010)	Swarm of autonomous robots applied to navigate and search an urban ground.	✓	✓	-	-	-	-	Onboard	✓	✓	Firefighting
	NIFTi (2010-2013)	Natural human-robot cooperation in dynamic environments for urban SAR.	✓	✓	-	✓	-	✓	-	-	-	Urban disasters
	Darius (2012-2015)	Integrated unmanned systems for urban, forest fires and maritime SAR.	✓	✓	✓	✓	✓	UAVs+UGVs +USV+UUV	Offboard	✓	-	Forest, urban and maritime
	ICARUS (2012-2016)	Development of robotic tools which can assist human SAR operators.	✓	✓	✓	✓	✓	UGV+UAVs +USV+UUV	Offboard	-	-	Practical SAR integration
	SEAGULL (2013-2015)	UAVs to support maritime situational awareness.	✓	-	-	✓	✓	-	Offboard	-	-	Maritime SAR
	TRADR (2013-2017)	Long-term human-robot teaming for response in industrial accidents.	✓	✓	-	✓	✓	✓	-	-	-	Industrial environments
	SmokeBot (2015-2018)	Robots with environmental sensors for disaster sites with low visibility.	-	✓	-	✓	-	-	✓	-	-	Fires and low visibility
	Centauro (2015-2018)	Mobility and dexterous manipulation in SAR by full-body telepresence.	✓	-	-	-	-	-	-	-	-	Harsh environments
	AutoSOS (2020-2022)	Multi-UAV system supporting maritime SAR with lightweight AI at the edge.	✓	-	✓	✓	✓	USV+UAVs	✓	✓	✓	Maritime
Competitions	**Robocup Rescue**	Challenges involved in SAR applications and promoting research collaboration.	✓	✓	✓	✓	✓	✓	Onboard+ offboard	✓	✓	Multiple environments
	DARPA Robotics	Human-supervised ground robots in dangerous, human-engineered environments.	✓	✓	-	-	-	UGVs	Onboard+ offboard	✓	-	Urban SAR
	DARPA SubT	Human-supervised subterranean robots for disaster-response operations.	✓	✓	-	✓	✓	UGVs+UAVs	Onboard+ offboard	✓	✓	Underground SAR
	ImPACT-TRC	Tough Robotics Challenge to aid in disaster response, recovery and preparedness.	✓	✓	-	✓	-	UAVs+UGVs	-	-	-	Earthquakes, tsunamis
	ERL-ESR	European Robotics League (ERL) Emergency Service Robots	✓	✓	✓	✓	✓	✓	✓	✓	✓	Urban multi-domain
	RESCON	Rescue Robot Contest for large-scale urban disasters	-	✓	-	-	-	-	✓	-	-	Earthquake body recovery
	OnShape	Teleoperated robots for disaster response. Student design challenge.	-	✓	-	-	-	-	-	-	-	Simulation
	ELROB	European Land Robot Trial: field robotics trials with UGVs.	✓	✓	-	-	-	UGVs	Onboard+ offboard	-	-	Autonomous UGVs

An early approach to the design and development of heterogeneous multi-UAV systems for cooperative activities was presented within the COMETS project (real-time coordination and control of multiple heterogeneous unmanned aerial vehicles) [15]. In terms of human-robot collaboration for SAR operations, one of the first EU funded projects in SAR robotics, PeLoTe [19]–[21], designed mobile robots for SAR missions and developed a heterogeneous telematic system for cooperative (human-robot) SAR operations. Other international projects designing and developing autonomous multi-robot systems for SAR operations include the NIFTi EU project (natural human-robot cooperation in dynamic environments) [16], ICARUS (unmanned SAR) [18], [22], TRADR (long-term human-robot teaming for disaster response) [17], [23], [24], or SmokeBot (mobile robots with novel environmental sensors for inspection of disaster sites with low visibility) [25], [26]. Other projects, such as CENTAURO (robust mobility and dexterous manipulation in disaster response by fullbody telepresence in a centaur-like robot), have focused on the development of more advanced robots that are not fully autonomous but controlled in real-time [14].

In COMETS, the aim of the project was to design and implement a distributed control system for cooperative activities using heterogeneous UAVs. To that end, the project researchers developed a remote-controlled airship and an autonomous helicopter and worked towards cooperative perception in real-time [6], [15], [27]. In NIFTi, both UGVs and UAVs were utilized for autonomous navigation and mapping in harsh environments [16]. The focus of the project was mostly on human-robot interaction and on distributing information for human operators at different layers. Similarly, in the TRADR project, the focus was on collaborative efforts towards disaster response of both humans and robots [17], and on multi-robot planning [23], [24]. In particular, the results of TRARD include a framework for the integration of UAVs in SAR missions, from path planning to a global 3D point cloud generator [28]. The project continued with the foundation of the German Rescue Robotics Center at Fraunhofer FKIE, where broader research is conduced, for example, in maritime SAR [29]. In ICARUS, project researchers developed an unmanned maritime capsule acting as a UUV, USVs, a large UGV, and a group of UAVs for rapid deployment. Also, mapping tools, middleware software for tactical communications, and a multi-domain robot command and control station [18]. While these projects focused on the algorithmic aspects of SAR operation, and on the design of multi-robot systems, in Smokebot the focus was on developing sensors and sensor fusion methods for harsh environments [25], [26]. A more detailed description of some of these projects, specially those that started before 2017, is available in [30].

In terms of international competition and tournaments, two relevant precedents in autonomous SAR operations are the European Robotics League (ERL) Emergency Tournament, and the RoboCup Rescue League. In [31], the authors describe the details of what was the world's first multi-domain (air, land and sea) multi-robot SAR competition. A total of 16 international teams competed with tasks including (i) environment reconnaissance and mapping (merging ground and aerial data), (ii) search for missing workers outside and inside an old building, and (iii) pipe inspection with localization of leaks (on land and underwater). The RoboCup Rescue League, on the other side, was proposed in 1999 [32]. One of the ground robots utilized in the 2020 edition is described in [33], a full-scale rescue robot with a robot arm equipped with a gripper.

Another set of major events featuring search and rescue robotics are the DARPA challenges. Humanoid robots [34] and human-robot coordination strategies [35] for SAR operations were presented in the 2013-2015 DARPA Robotics Challenge. The DARPA Subterranean (SubT) Challenge, running in 2018-2021, has shifted the focus towards underground MRS for SAR operations, with ground robots and UAVs collaborating in the tasks [36]. This challenge has demonstrated the versatility and significant increase of flexibility of heterogenous MRS [37], with robust UAV flight in inherent constrained environments [38], and ground robots able of navigating complex environments and long-term autonomy [39]. In 2020, due to the Covid-19 pandemic, the challenge moved to a fully virtual edition with realistic simulation-based environments [40].

III. MULTI-ROBOT SAR: SYSTEM-LEVEL PERSPECTIVE

Robotic SAR systems can differ in multiple ways: their intended operational environment (e.g., urban, maritime, or wilderness), the amount and type of robots involved (USVs, UAVs, UGVs, UUVs), their level of autonomy, and the ways in which humans control the robotic systems, among other factors. This section aims at introducing the main components to consider when designing an MRS for SAR operations, from communication networks to the detection of victims, and considering also specific requirements of different operational environments

A. SYSTEM REQUIREMENTS AND EQUIPMENT USED

Here we describe the different types of SAR robots in the literature and the most common onboard sensor suites.

1) GROUND ROBOTS

Two complimentary examples of ground robots for SAR operations are introduced in [41], where both large and small robots are described. Ground robots for SAR missions can be characterized among those with dexterous manipulation capabilities and robust mobility on uneven terrain, such as the robot developed within the CENTAURO project [14], smaller robots with the ability of moving through tight spaces [41], or serpentine-like robots able of tethered operation across complex environments [42]. The recent DARPA SubT challenge has seen the design and deployment of flexible and robust ground units able of long-term autonomy and carry aerial units. For instance, the CTU-CRAS team, achieving the best non-DARPA-funded performance in the tunnel track,

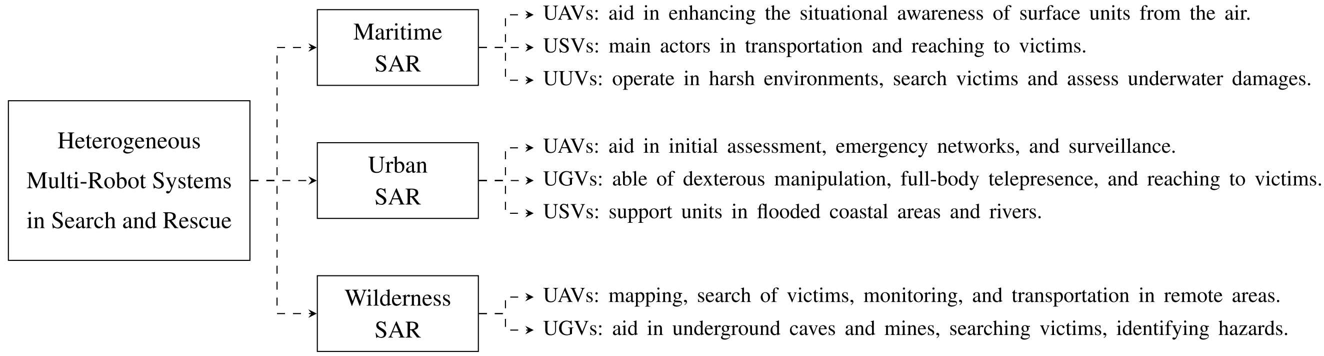


FIGURE 3. Types of autonomous robots utilized in different SAR scenarios and their main advantages.

utilized a Husky A200 (wheeled robot), two Absolem platform (tracked robot with four flippers), and six-legged PhantomX Mark II platforms (crawling hexapod robots) [36].

2) AERIAL ROBOTS

In terms of aerial robots, UAVs can be quadrotors, fixed-wing aircrafts, or of other types (e.g., blimps). A representative example of a quadrotor is available in [28], where the authors introduce a platform for instantaneous UAV-based 3D mapping during SAR missions. The platform offers a complete sensor suite. The main sensors are a 16-channel laser scanner, an infrared camera for thermal measurements, an RGB camera, and inertial/positional sensors for GNSS and altitude estimation. The UAV, a DJI S1000+ octocopter, is connected to a ground station on-board a fire fighter command vehicle with a custom radio link capable of over 300 Mbps downlink speed at distances up to 300 m. The system is able to produce point clouds colored both by reflectance (from the laser measurements) and temperature (from the infrared camera). This suite of sensors is one of the most complete for UAVs, except for the lack of ultrasonic sensors. In general, however, cameras are the predominant sensors owing to their flexibility, size and weight. Examples of autonomous quadrotors, fixed-wing and rotatory-wing vehicles equipped with GNSS sensors and RGB cameras for search of people in emergency scenarios are available in [43]–[45]. A description of different types of aerial SAR robots utilized within the ICARIUS project is available in [46], and a survey on UAVs for SAR operations by Grogan *et al.* shows the predominance of RGB cameras as the main or only sensor in use, without considering inertial and GNSS units [10]. Most of these and other works, however, assume the aerial robots move in large spaces and are not excessively constrained by environmental conditions (e.g., smoke, wind, or low-light). The DARPA SubT challenge provides again examples of robots being designed for more challenging environments. In [39], the authors present Duckiefloat, a collision-tolerant blimp for long-term autonomy in underground environments. The CTU-CRAS team utilized quadrotors based on the F450 kit by DJI, with a Bluefox RGB camera and ambient illumination from an LED stripe [36].

3) SURFACE AND UNDERWATER ROBOTS

Maritime SAR operations often involve both surface and underwater robots, with support UAVs. Descriptions of different surface robots offering an overview of existing solutions are available in [47] and [48]. Some particularities of maritime SAR robots include the use of seafloor pressure sensors, seismometers, and hydrophone for the detection of tsunamis and earthquakes, or sensors for measuring meteorological variables and water conditions (e.g., temperature, salinity, depth, pH balance and concentrations of different chemicals). Other examples include sensors for various liquids and substances for robots utilized in oil spills or contaminated waters (e.g., laser fluorosensors).

4) INTEROPERABILITY

A significant challenge in SAR robotics, owing to the specialization of robots in specific tasks, is interoperability. The ICARUS and DARIUS projects have both worked towards the integration of different unmanned vehicles or robots for SAR operations [30], [49]. Interoperability is particularly important in heterogeneous multi-robot systems, where data from different sources needs to be aggregated in real-time for efficient operation and fast actuation. Furthermore, because robots in SAR operations are mostly supervised or partly teleoperated, the design of a ground station is an essential piece in a complete SAR robotics system. This is even more critical when involving the control of multi-robot systems. The design of a generic ground station able to accommodate a wide variety of unmanned vehicles has been one of the focuses of the DARIUS project [50]. The approach to interoperability taken within the ICARIUS project is described in detail in [51]. The project outcomes included a library for multi-robot cooperation in SAR missions that assumes that the Robot Operating System (ROS) is the middleware utilized across all robots involved in the mission. ROS is the de facto standard in robotics industry and research [52]. In [51], the authors also characterize typical robot roles, levels of autonomy for different types of robots, levels of interoperability, and robot capabilities.

B. OPERATIONAL ENVIRONMENT

In this subsection, we characterize the main SAR environments (urban, maritime and wilderness) and discuss how the different challenges in each of these types of scenarios have been addressed in the literature. The main considerations are summarized in Table 3.

1) MARITIME SAR

Search and rescue operations at sea were characterized by Zhao *et al.* in [61]. The paper emphasizes that maritime accidents tend to happen suddenly. Some of the most significant factors are injury condition, possession of location devices and rescue equipment, and environmental factors such as geographic position, wave height, water temperature, wind speed and visibility. A considerable amount of accidents happen near the shoreline with favorable weather conditions, such as beaches during the summer. Robotic SAR systems can be ready to act fast. For instance, Xian *et al.* designed a life-ring drone delivery system for aiding people near the shore [66].

The main types of autonomous robots utilized in maritime SAR operations are USVs and UUVs [22], together with support UAVs [67]. Sea SAR operations are one of the scenarios where heterogeneous multi-robot systems have been already widely adopted [67]. A representative work on the area, showing a heterogeneous and cooperative multi-robot system for SAR operations after ship accidents, was presented by Mendoça *et al.* [60]. The authors proposed the utilization of both a USV and UAV to find shipwreck survivors at sea, where the USV would carry the UAV until it arrives near the shipwreck location.

The combination of USVs and UUVs has also been widely studied, with or without UAVs. Some of the most prominent examples in this direction come from the euRathlon competition and include solutions from the ICARUS project [48]. The surface robot was first utilized to perform an autonomous assessment, mapping and survey of the area, identifying points of interest. Then, the underwater vehicle was deployed to detect pipe leaks and find victims underwater.

2) URBAN SAR

Urban SAR scenarios include, among others, natural disasters (e.g., earthquakes), large fires, or accidents involving hazardous materials. USAR robots increase the safety of rescue personnel by reducing their exposure to potential hazards in the site and providing an initial assessment of the situation. For instance, in [28], the authors describe a heterogeneous multi-UAV system focused at providing an initial assessment of the environment through mapping, object detection and annotation, and scene classifier.

Novel types of robotic systems have also been developed to better adapt to the challenges of USAR environments. To be able to utilize UAVs near fires, Myeong *et al.* presented FAROS, a fireproof drone for USAR operations [68]. Other robots have taken inspiration from video scopes and fiber scopes utilized to obtain imagery from confined spaces [69], [70]. In [42], researchers participating in the ImPACT-TRC challenge presented a thin serpentine robot platform, a long and flexible continuum robot with a length of up to 10 m and a diameter of just 50 mm, able to localize itself with visual SLAM and access collapsed buildings.

3) WILDERNESS SAR

In wilderness SAR (WiSAR) operations, the literature often includes SAR in mountains [62], underground mines and caves [64], [65], [71], and forests and other rural or remote environments [43], [72], [73]. The need for heterogeneous MRS in WiSAR environments has been made evident during the DARPA SubT challenge [36], [37].

One of the most common SAR operations in mountain environments occurs in a post-avalanche scenario. In areas with a risk of avalanches, mountaineers often carry avalanche transmitters (AT). UAVs prepared for harsh conditions (strong winds, high altitude and low temperatures) have been utilized for searching ATs [62]. In [63], an autonomous multi-UAV system for localizing avalanche victims was developed.

Forest environments also present significant challenges from the perception point of view, due to the density of the environments and lack of structure for path planning [74]. WiSAR operations might involve tracking a moving target (a lost person), and thus the search area increases through time [72].

Another specific scenario that has attracted research attention is SAR for mining applications [64]. Two specific challenges in SAR operations in underground environments are the limitations of wireless communication and the existence of potentially toxic gases. Ranjan *et al.* have presented an overview of wireless robotic communication networks for underground mines [71]. The DARPA SubT challenge has provided an opportunity for developing novel multi-robot communication techniques and including the utilization of breadcrumb nodes [75].

C. TRIAGE

In a scene of an accident or a natural disaster, an essential step once victims are found is to follow a triage protocol. Triage is the process through which victims are pre-assessed. In [76], the authors explored from the perspective of medical specialists how robots could interact with victims and perform an autonomous triage. In [77], the focus was on analyzing the potential benefits and challenges in robotics technology to assess those vital signs in an autonomous manner.

D. SHARED AUTONOMY AND HUMAN-SWARM INTERACTION

In multi-robot systems and robots involving complex manipulation (e.g., humanoids) with a high number of degrees of freedom, such as humanoids, the concept of shared autonomy gains importance. Shared autonomy refers to the autonomous control of the majority of degrees of freedom in a system, while designing a control interface for human operators to control a reduced number of parameters defining the global behavior of the system [78]. For instance, in [79] the

TABLE 3. Challenges and Opportunities for Autonomous Robots in different types of environments: Urban SAR [28], [42], [53]–[58], Maritime SAR [12], [22], [59]–[61], and Wilderness SAR [62]–[65].

	Challenges	Opportunities
Maritime SAR	(i) Visual detection of people at sea, with potentially vast areas to search and comparatively small targets to detect. (ii) The need for long-distance operation, with either high levels of autonomy or real-time communication in remote environments. (iii) Underwater robots often rely on tethered communication or need to resurface to share their findings. (iv) Localization and mapping underwater presents significant challenges owing to the transmission characteristics in water of light and other electromagnetic waves used in more traditional sensing methods. (v) Motion affected by marine currents, waves and limited water depths.	(i) UAVs can provide a significant improvement at sea in term of situational awareness from the air, and can be deployed on-site even from small ships. (ii) Heterogeneous multi-robot systems can aid in multi-modal coordinated search aggregating information from the different perspectives (aerial, surface, underwater). (iii) Disposable or well-adapted USVs and UUVs can be utilized in harsh environments or bad weather conditions when SAR operations at sea are interrupted for safety reasons.
Urban SAR	(i) The presence of hazardous materials, radiation areas, or high temperatures. (ii) Localization and mapping of unknown, unstructured, dense and hazardous environments that result from disasters such as earthquakes or explosions, and in which robots are meant to operate. (iii) Navigation in narrow spaces and uneven terrain, being able to traverse small apertures and navigate over unstable debris. (iv) Close cooperation with human operators in a potentially shared operation space, requiring for well defined human-robot interaction models.	(i) Relieving human personnel from emotional stress and physical threats (e.g., radiation, debris). (ii) Reducing the time for locating survivors. Mortality in USAR scenarios raises significantly after 48 h. (iii) Assessing the structural parameters of the site and assisting on remote or semi-autonomous triage. (iv) Detecting and locating survivors and analyzing the surrounding structures. (v) Establishing a communication link to survivors.
Wilderness SAR	(i) In avalanche events, robots often need to access remote areas (long-term operation) while in harsh weather conditions (e.g., low temperatures, low air pressure, high wind speeds). (ii) Exploration of underground mines and caves presents significant challenges from the point of view of long-term localization and communication. (iii) SAR operations to find people lost while hiking or climbing mountains often occur in the evening or at night, when visibility conditions make it more challenging for UAVs or other robots to identify objects and people. (iv) WiSAR operations often involve tracking of a moving target, with a search area that expands through time.	(i) After an avalanche, areas that are hard to reach by land can be quickly surveyed with UAVs. (ii) SAR personnel in mines or caves can rely on robots for environmental monitoring, mainly toxic gases, and avoid hazardous areas. (iii) UAVs equipped with thermal cameras can aid in the search of lost hikers or climbers at night, and relay communication from SAR personnel. (iv) Multi-robot systems can build probabilistic maps for movable targets and revisit locations more optimally.

authors describe the design principles followed in the DARPA Robotics Challenge to give the operators of a humanoid robot enough situational awareness while simplifying the actual control of the robot via predefined task sequences.

Another research direction in the control of MRS is human-swarm interaction. Within the EU Guardians project, researchers explored the possibilities of human-swarm interaction for firefighting, and defined the main design ideas in [80].

In the DARPA SubT challenge, the rules allow only one human to communicate with the multi-robot team. A hybrid autonomous/semi-autonomous model has been proposed in [36], with UAVs being fully autonomous and the larger UGVs could be directly operated in adverse conditions, but are semi-autonomous otherwise.

E. COMMUNICATION

Communication plays an vital role in an MRS due to the need of coordination and information sharing necessary to carry out collaborative tasks. In multi-agent systems, a mobile ad-hoc network (MANET) is often formed for wireless communication and routing messages between the robots. Owing to the changing characteristics in terms or wireless transmission in different physical mediums, different communication technologies are utilized for various types of robots. An overview of the main MRS communication technologies is available in [81], while a review on MANET-based communication for SAR operations is available in [82].

Collaborative MRS need to be able to communicate to keep coordinated, but also need to be aware of each other's position in order to make the most out of the shared data [83], [84]. Situated communication refers to wireless communication technologies that enable simultaneous data transfer while locating the data source [85]. Ubiquitous wireless technologies such as WiFi and Bluetooth have been exploited to enable localization [86]–[92]. These approaches have been traditionally based on the received signal strength indicator (RSSI) and the utilization of either Bluetooth beacons in known locations [89]–[91], or radio maps that define the strength of the signal of different access points over a predefined and surveyed area [86], [88]. More recently, other approaches rely on angle-of-arrival [87], now built-in in Bluetooth 5.1 devices [93]. Ultra-wideband (UWB) technology has emerged as a more accurate and less prone to interference alternative to Wi-Fi and Bluetooth [94]. With most existing research relying on fixed UWB transceivers in known locations [95], recent works also show promising results in mobile positioning systems or collaborative localization [96]. A recent trend has also been to apply deep learning in positioning estimation [97].

From the point of view of multi-robot coordination, maintaining connectivity between the different agents participating in a SAR mission is critical. Connectivity maintenance in wireless sensor networks has been a topic of study for the past two decades [98]. In recent years, it has gained more attention in the fields of MRS with decentralized approaches [99]. Connectivity maintenance algorithms can be designed coupled with distributed control in multi-robot systems [100], or collision avoidance [101]. Xiao *et al.* have recently presented a cooperative multi-agent search algorithm with connectivity maintenance [102]. Similar works aiming at cooperative search, surveillance or tracking with multi-robot systems focus on optimizing the data paths [103] or fallible robots [104], [105]. Another recent work in area coverage with connectivity maintenance is available in [106]. A comparison of local and global methods for connectivity maintenance of multi-robot networks from Khateri *et al.* is available in [107].

In environments with limited connectivity, building and maintaining communication maps with information about the coverage and reliability of communication in different areas brings evident benefits. To this end, Amigomi *et al.* have presented a method for updating communication maps in an online manner under connectivity constraints [108]. A survey on multi-robot exploration of communication-restricted environments is available in [109].

F. LOCALIZATION AND DEPLOYMENT IN GNSS-DENIED ENVIRONMENTS

Localization is one of the main challenges in the deployment of mobile robots. Localization approaches can be divided among those providing global localization, and others focusing on relative localization (odometry) with respect to the initial position during deployment. The former case is most notably represented by GNSS sensors. However, SAR operations can also occur in GNSS-denied environments (e.g., underground, indoor fires) or environments where GNSS sensors do not provide enough accuracy (e.g., dense urban environments or forests). Global localization with other onboard sensors can be achieved with image matching [110], or lidar data matching [111].

Among the different approaches to onboard odometry, visual methods have gained significant traction due to their low price, passive nature and flexibility [112]. This is the case, for instance, of visual-inertial odometry with either monocular cameras [113], or multiple sensors [114]. However, these sensors present limitations in challenging environments with low-light or low-visibility conditions. In dense urban environments, lidar-based odometry is the only viable solution for long-term autonomy if high-accuracy localization is required [115].

Simultaneous Localization and Mapping (SLAM) approaches utilize odometry algorithms to build local maps [116], [117], while utilizing those maps later on for more stable and global localization, where now the global term refers to the scope of the mission since deployment, or since the process of building the map started. The different teams participating in the DARPA SubT challenge have employed various SLAM approaches with both lidar-based and vision-based approaches. Some of the specific algorithms have been ORB-SLAM in [39], or Hector SLAM [36].

IV. MULTI-ROBOT COORDINATION

In this section, we describe the main algorithms required for multi-robot coordination and planning in collaborative applications. These are key enablers of MRS capabilities in terms of exploration and navigation over large areas. We discuss this mainly from the point of view of cooperative multi-robot systems, while focusing on their applicability towards SAR missions. The main problems discussed in this section are the following:

- *Multi-robot task allocation*: distribution of tasks and objectives among the robots (e.g., areas to be searched, or positions to be occupied to ensure connectivity among the robots and with the base station)
- *Path planning and area coverage*: global path planning covers area coverage (generation of paths to entirely analyze a given area) and area partition (dividing the area between multiple robots). Local planning and deals mainly with obstacle and collision avoidance, incorporating robot dynamics.
- *Area exploration*: coverage and mapping algorithms (or discover/ search for specific objects) in potentially unknown environments.
- *Centralized multi-robot planning*: decision-making on the actions of multiple robots by either gathering and processing data in a single node, from which decisions are distributed to others, or by achieving consensus through communication (often requiring agents to be aware of all others, and stable communication).
- *Distributed multi-robot planning*: algorithms enabling agents to make independent decisions individually or in subsets based only on their own data or data shared by their neighbors. These do not necessarily need agents to be aware of the existence or state of all other agents in the system.

A. MULTI-ROBOT TASK ALLOCATION

Search and rescue operations with multi-robot systems involve aspects including collaborative mapping and situational assessment [118], distributed and cooperative area coverage [119], or cooperative search [120]. These or other cooperative tasks involve the distribution of tasks and objectives within the MRS. In a significant part of the existing multi-robot SAR literature, this is predefined or done in a centralized manner [6], [16], [18], [28]. Here, we discuss instead distributed multi-robot task allocation algorithms that can be applied to SAR operations. Distributed algorithms have the general advantage of being more robust in adverse environments against the loss of individual agents or when the communication with the base station is unstable.

A comparative study on task allocation algorithms for multi-robot exploration was carried out by Faigl *et al.* in [121], considering five distinct strategies: greedy assignment, iterative assignment, Hungarian assignment, multiple traveling salesman assignment, and MinPos. However, most of these approaches are often centralized from the decision-making point of view, even if they are implemented in a distributed manner. Others, such as MinPos, shift between the two modalities depending on the availability of communication. Successive works have been presenting more decentralized methods. Decentralized task allocation algorithms for autonomous robots are very often based on market-based approaches and auction mechanisms to achieve consensus among the agents [122]–[125]. Both of this approaches have been extensively studied for the past two decades within the multi-robot and multi-agent systems communities [126], [127]. Bio-inspired algorithms have also been widely studied within the multi-robot and swarm robotics domains. For instance, in [128], Kurdi *et al.* present a task allocation algorithm for multi-UAV SAR systems inspired by locust insects. Active perception techniques have also been incorporated in multi-robot planning algorithms in existing works [129], [130].

An early work in multi-robot task allocation for SAR missions was presented by Hussein *et al.* [122], with a market-based approach formulated as a multiple traveling salesman problem. The authors applied their algorithm to real robots with simulated victim locations that the robots had to divide among themselves and visit. The solution was optimal (from the point of view of distance traveled by the robots) and path planning for each of the robots was also taken into account. The authors, however, did not study the potential for scalability with the number of robots or victim locations, or consider the computational complexity of the algorithm. In that sense, and with the aim of optimizing the computational cost owing to the non-polynomial complexity nature of optimal task allocation mechanisms, Zhao *et al.* presented a heuristic approach [123]. The authors introduced a significance measure for each of the tasks, and utilized both victim locations and terrain information as optimization parameters within their proposed methodology. The algorithm was tested under a simulation environment with a variable number of rescue robots and number of survivor locations to test the scalability and optimality under different conditions.

An auction-based approach aimed at optimizing a cooperative rescue plan within multi-robot SAR systems was proposed by Tang *et al.* [124]. In this work, the emphasis was also put on the design of a lightweight algorithm more appropriate for ad-hoc deployment in SAR scenarios.

A different approach where a human supervisor was considered appears in [131]. Liu *et al.* presented in this work a methodology for task allocation in heterogeneous multi-robot systems supporting USAR missions. By relying on a supervised system, the authors show better adaptability to situations with robot failures. The algorithm was tested under a simulation environment where multiple semi-autonomous robots were controlled by a single human operator.

B. AREA COVERAGE AND PATH PLANNING

An essential part of autonomous SAR operations is path planning and area coverage. To this end, multiple algorithms have been presented for different types of robots or scenarios.

Planning in SAR scenarios can pose additional challenges to well-established planning strategies for autonomous robots. In particular, the locations of victims trapped under debris or inside cave-like structures might be relatively easy to determine but significantly complex to access, thus requiring specific planning strategies. In [120], Suarez *et al.* present a survey of animal foraging strategies applied to rescue robotics. The main methods that are discussed are directed search (search space division with memory- and sensory-based search) and persistent search (with either predefined time limits or constraint-optimization for deciding how long to persist on the search). With specialized robots being used for different scenarios (e.g., tracked robots or crawling robots), the ability of these robots to traverse different environments might not be known a priori. To address this issue, ML-based techniques that rely on online learning have been utilized to create cost maps of the environment in terms of the ease of movement. In [132], the authors introduce a method for a fully autonomous hexapod walking robot tested on a laboratory track with uneven terrain.

Path planning algorithms can be part of area coverage algorithms or implemented separately for robots to cover their assigned areas individually. In any case, when area coverage algorithms consider path planning, it is often from a global point of view, leaving the local planning to the individual agents. A detailed description of path planning algorithms including approaches of linear programming, control theory, multi-objective optimization models, probabilistic models, and meta-heuristic models for different types of UAVs is available in [133]. While some of these algorithms are generic and only take into account the origin and objective position, together with obstacle positions, others also consider the dynamics of the vehicles and constraints that these naturally impose in local curvatures, such as Dubin curves [133].

Area coverage and path planning algorithms take into account mainly the shape of the objective area to be surveyed. Nonetheless, a number of other variables are also considered in more complex algorithms, such as energy consumption, range of communication and bandwidth, environmental conditions, or the probability of failure. This data is not necessarily available a priori, and therefore it is also in the interest of the robots to collect data affecting the planning outcome while operating. The problem of maximizing the utility of data collection is called the informative path planning (IPP) problem [134]. IPP approaches have been shown to outperform more traditional planning algorithms such as greedy algorithms and genetic algorithms [135].

The specific dynamics and capabilities of the robots being used can also be utilized to optimize the performance of the area coverage, for example when comparing the maneuverability of quadrotors and fixed-wing UAVs. Cabreira *et al.*

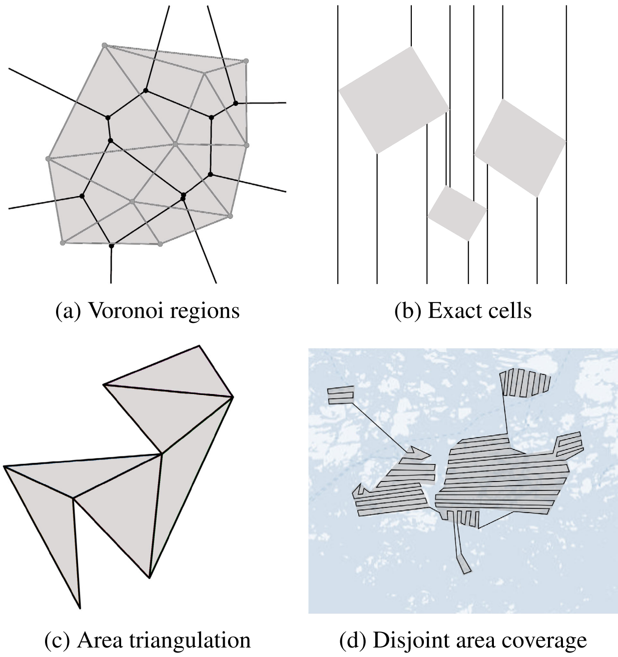


FIGURE 4. Illustration of different basic area decomposition and coverage algorithms: (i) decomposition through voronoi regions, (ii) exact cell decomposition, (iii) polygonal decomposition (triangular in this case), and (iv) disjoint area coverage. The resulting decompositions or coverage paths are marked with black lines, while the original areas are shown in gray colors.

have presented algorithms for coverage path planning with UAVs [136].

Area coverage algorithms can be broadly classified in terms of the assumptions they make on the geometry of the area to be covered. The most basic approaches consider only convex and joint areas [119], for which paths can be efficiently generated based on area decomposition algorithms [137], [138]. Some of the most common area decomposition and coverage algorithms are shown in Fig. 4.

Recent works have considered more complex environments. For instance, in [139], Xie *et al.* presented a path planning algorithm for UAVs covering disjoint convex regions. The authors' method considered an integration of both coverage path planning and the traveling salesman problem. In order to account for scalability and real-time execution, two approaches were presented: a near-optimal solution based on dynamic programming, and a heuristic approach able to efficiently generate high-quality paths, both tested under simulation environments. Also aiming at disjoint but convex areas, Vazquez *et al.* proposed a similar method that separates the optimization of the order in which the different areas were visited and the path generation for each of them [140]. Both of this cases, however, provide solutions for individual UAVs.

Furthermore, the optimization problems upon which multi-robot area coverage algorithms build are known to belong to the NP-hard class of non-deterministic polynomial time algorithms [141]. Therefore, part of the existing research has focused towards probabilistic approaches. This naturally fits to SAR operations since, after an initial assessment of the environment, SAR personnel can get an a priori idea of the most probable locations for victims [142]. The idea of using probability distributions in the multi-objective search optimization problem has also been extended towards actively updating these distributions as new sensor data becomes available [143].

C. PLANNING FOR DIFFERENT ROBOTS: UAVs, UGVs, UUVs AND USVs

Mobile robots operating on different mediums necessarily have different constraints and a variable number of degrees of freedom. For local path planning, a key aspect to consider when designing control systems is the holonomic nature of the robot. In a holonomic robot, the number of controllable degrees of freedom is equal to the number of degrees of freedom defining the robot's state. In practice, most robots are non-holonomic, with some having significant limitations to their local motion such as fixed-wing UAVs [144], or USVs [145]. However, quadrotor UAVs, which have gained considerable momentum owing to their flexibility and relatively simple control, can be considered holonomic [146]. Ground robots equipped with omniwheel mechanisms and able of omnidirectional motion can be also considered holonomic if they operate on favorable surfaces [147].

Multiple works have been devoted to reviewing the different path planning strategies for unmanned vehicles in different mediums: aerial robots [133], surface robots [148], underwater robots [149], [150], and ground robots for urban [55], or wilderness [151] environments. From these works, we have summarized the main constraints to be considered in path planning algorithms in Fig. 5.

The main limitations in robot navigation, and therefore path planning, in different mediums can be roughly characterized by: (i) dynamic environments and movement limitations in ground robots; (ii) energy efficiency, situational awareness, and weather conditions in aerial robots; (iii) underactuation and environmental effects in surface robots, with currents, winds and water depth constraints; and (iv) localization and communication in underwater robots. Furthermore, these constraints increase significantly in SAR operations, with earthquakes aggravating the movement limitations of UGVs, or fires and smoke preventing normal operation of UAVs. Some emergency scenarios, such as flooded coastal areas, combine multiple of the above mediums making the deployment of autonomous robots even more challenging. For instance, in [152], the authors describe path planning techniques for rescue vessels in flooded urban environments, where many of the limitations of urban navigation are added to the already limited navigation of surface robots in shallow waters.

A key parameter to take into account in autonomous robots, and particularly in UAVs, is energy consumption. Di Franco *et al.* presented an algorithm for energy-aware path planning with UAVs [153]. A more recent work considering energy-aware path planning for area coverage introduces a novel algorithm for path planning that minimizes turns [154]. Energy efficiency is a topic that has also been considered in USVs. In [155], the authors introduced an energy-efficient 3D (two-dimensional positioning and one-dimension for orientation) path planning algorithm that would take into account both environmental effects (marine currents, limited water depth) and the heading or orientation of the vehicle (in the start and end positions).

Owing to the flexibility of quadrotor UAVs, they have been utilized with different roles in more complex robotic systems. For instance, in [13] the authors describe a heterogeneous multi-UAV system for earthquake SAR where some of the UAVs are in charge of providing reliable network connection, as a sort of air communication station, while smaller UAVs flying close to the ground are in charge of the actual search tasks.

D. MULTI-ROBOT PATH PLANNING

Research in the field of multi-robot path planning has been ongoing for over two decades. An early approach to multi-robot cooperation was presented in [156] in 1995, where the authors introduced an incremental plan-merging approach that defined a global plan shared among the robots. In [137], an early generalization of previous algorithms towards nonconvex and nonsimply connected areas was presented, enabling deployment in more realistic scenarios. The advances since then have been significant in multiple directions. With the idea or providing fault-tolerant systems, in [119] the authors introduced a reconfiguration process that would account in real-time for malfunctioning or missing agents, and adjust the paths of remaining agents accordingly. Considering the need of inter-robot communication for aggregating and merging data, a cooperative approach to multi-robot exploration that considers the range limitations of the communication system between robots was introduced in [157]. Non-polygonal area partitioning methods have also been proposed. In [158], a circle partitioning method that the authors claim to be applicable to real-world SAR operations was presented. Covering the topics of connectivity maintenance and IPP, a multi-robot IPP approach to managing continuous connectivity constraints appears in [159].

Existing approaches often differentiate between area coverage and area exploration. In area coverage algorithms, algorithms focus on optimally planning paths for traversing a known area, or dividing a known area among multiple agents to optimize the time it takes to analyze it. Area exploration algorithms focus instead on the coverage and mapping of potentially unknown environments. The two terms, however, are often used interchangeably in the literature. An overview and comparison of multi-robot area exploration algorithms is available in [160].

In [161], Choi *et al.* present a solution for multi-UAV systems, which is in turn focused at disaster relief scenarios. In particular, the authors developed this solution in order to improve the utilization of UAVs when fighting multiple wildfires simultaneously. Also considering multi-UAV path planning, but including non-convex disjoint areas, Wolf *et al.* proposed a method were the operator could input a desired overlap in the search areas [162]. This can be of particular interest in heterogeneous multi-robot systems where different robots have different sensors, and the search personnel wants multiple robots to travel over some of the areas. Finally, another recent work in cooperative path planning that focuses on mountain environments and can be of specific interest in WiSAR operations was presented by Li *et al.* [163].

A subset of multi-robot path planning algorithms are formation control algorithms. Formation control or pattern formation algorithms are those that define spatial configurations in multi-robot systems [164]. Most formation control algorithms for multi-agent systems can be roughly classified in three categories from the point of view of the variables that are measured and actively controlled by each of the agents: position-based control, displacement-based control, and distance or bearing-based control [164]. Formation control algorithms requiring global positioning are often implemented in a centralized manner, or through collaborative decision making. Displacement and distance or bearing-based control, on the other hand, enable more distributed implementations with only local interactions among the different agents [165]–[167]. In SAR operations, formation control algorithms are an integral part of multi-robot ad-hoc networks or MANETs [168], [169], multi-robot emergency surveillance and situational awareness networks [170], or even a source of communication in human-swarm interaction [171].

E. MULTI-OBJECTIVE MULTI-AGENT OPTIMIZATION

From a theoretical point of view, a multi-agent collaborative search problem can be formulated and solved as a multi-agent and multi-objective optimization problem in a certain space [172], [173].

In post-disaster scenarios and emergency situations in general, an initial assessment of the environment often provides rescue personnel an idea of the potential spatial distribution of victims [13]. In those cases, different a priori probabilities can be assigned to different areas, providing a ranking of locations for the multi-objective optimization problem. The literature involving multi-agent multi-objective optimization for SAR operations is, however, sparse. In [174], Hayat *et al.* proposed a genetic algorithm for multi-UAV search in a bounded area. One of the key novelties of this work is that the authors consider simultaneously connectivity maintenance among the UAV network and optimization of area coverage. Moreover, the algorithm could be adjusted to give more priority to either coverage or connectivity, depending on the mission requirements. A multi-objective evolutionary algorithm aimed at general emergency response planning was proposed by Narzisi *et al.* in [175].

F. PLANNING IN HETEROGENEOUS MULTI-ROBOT SYSTEMS

Most existing approaches for multi-robot exploration or area coverage either assume that all agents share similar operational capabilities, or that the characteristics of the different

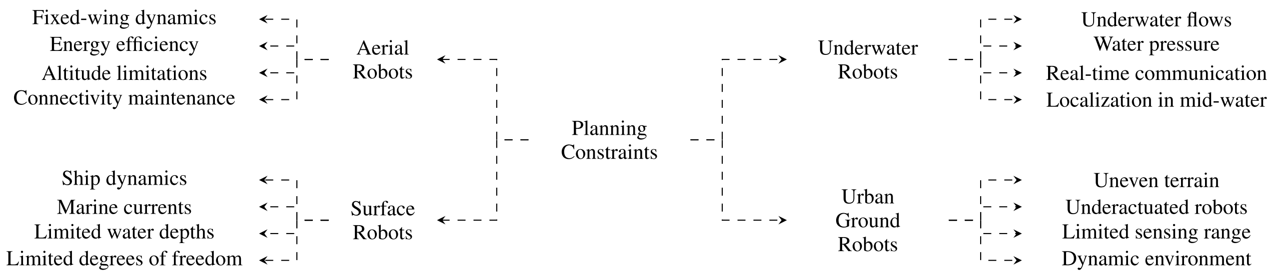


FIGURE 5. Main path planning constraints that autonomous robots in different domains need to account for. Some of these aspects are common across the different types of robots, such as energy efficiency and inherent constraints from the robots' dynamics, but become more predominant in UAVs and USVs, for instance.

agents are known a priori. Emergency deployments in post-disaster scenarios for SAR of victims, however, requires flexible and adaptive systems. Therefore, algorithms able to adapt to heterogeneous robots that potentially operate on different mediums and with different constraints (e.g., UAVs and UGV collaborating in USAR scenarios) need to be utilized. In this direction, Mueke *et al.* presented a system-level approach for distributed control of heterogeneous systems with applications to SAR scenarios [176]. In general, we see a lack of further research in this area, as most existing projects and systems involving heterogeneous robots predefine the way in which they are meant to cooperate. From a more general perspective, an extensive review on control strategies for collaborative area coverage in heterogeneous multi-robot systems was recently presented by Abbasi [177]. Also from a general perspective, a survey on cooperative heterogeneous multi-robot systems by Rizk *et al.* is available in [178].

V. SINGLE AND MULTI-AGENT PERCEPTION

In SAR missions, it is essential to be able to quickly detect humans, hazards, and provide real-time situational awareness to the robots. In [181], the authors provide a broad overview of the progress of computer vision covering all sorts of emergencies. Current state-of-the-art computer vision models are based on Deep Learning (DL), which often leads to heavy and slow methods that cannot operate on real-time on portable devices. However, recent research has also focused towards the development of lighter and faster models able to operate in real-time with limited hardware resources.

This section thus focuses on DL for real-time perception with lightweight models. We review single and multi-agent machine perception methods on SAR-like missions and environments, where DL is the key enabler for the actual identification of victims and assessment of the situation. As cameras are the most common sensors in SAR robotics, we first concentrate on image-based perception, i.e., semantic segmentation and object detection. In semantic segmentation, everything that the agent perceives is labeled, and in object detection, only the objects of interest are labeled. The difference is illustrated in Fig. 6. We also discuss multi-modal sensor fusion that allows to combine information from cameras and other sensors.

A. SEMANTIC SEGMENTATION

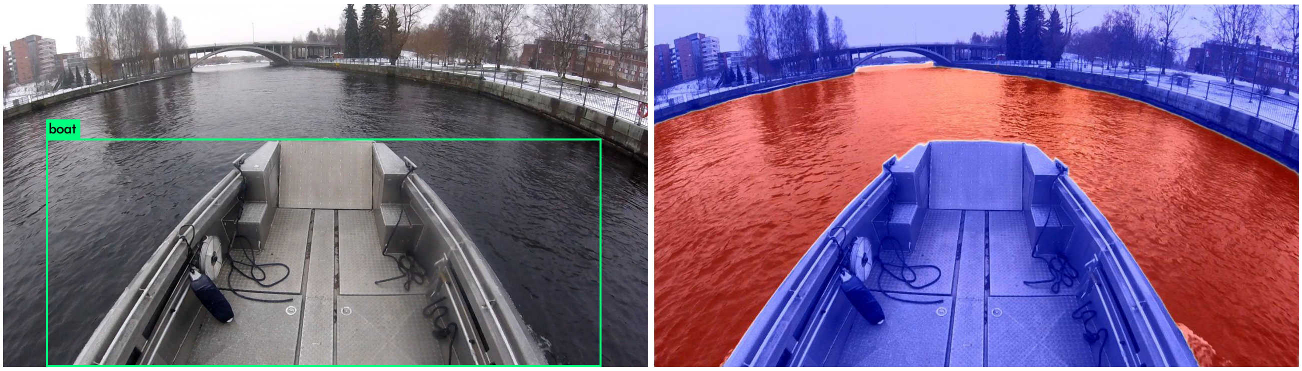
Semantic segmentation is a process, where each pixel in an image is linked to a class label, such as sky, road, or forest. These pixels then form larger areas of adjacent pixels that are labeled with the same class label and recognized as objects. A survey on semantic segmentation using deep learning techniques available in [182] provides an extensive view of the methods provided to tackle this problem. In autonomous agents in general, the use of semantic segmentation has been studied fairly well in autonomous road vehicles. Siam *et al.* [183] have done an in-depth comparison of such semantic segmentation methods for autonomous driving and proposed a real-time segmentation benchmarking framework.

In marine environment, the study of semantic segmentation has been less common. In [184], three commonly used state-of-the-art deep learning semantic segmentation methods (U-Net [185], PSP-Net [186] and DeepLabv2 [187]) are benchmarked on a maritime environment. The leaderboard for one of the largest publicly available datasets, Modd2 [188], also contains a listing of semantic segmentation method capable to perform in marine environment [186], [187], [189]–[194].

In our former studies [180], [195], we have focused on semantic segmentation to separate water surface from everything else that appears in the image, which is similar to the process that is performed in self-driving cars for road detection. While excellent results can be obtained when the algorithm is applied in conditions that resemble the training images (see Fig 6b), it was observed the performance decreases notably in different conditions. This highlights the need of diverse training images and domain adaption techniques that help to adjust to unseen conditions [196].

B. OBJECT DETECTION

Object detection is a technique related to computer vision and image processing which deals with detecting instances of semantic objects of a certain class in digital images and videos. Object detectors can usually be divided into two categories: two-stage detectors and one-stage detectors. Two-stage detectors first propose candidate object bounding boxes, and then features are extracted from each candidate box for the following classification and bounding-box regression tasks. The one-stage detectors propose predicted boxes from input images directly without region proposal



(a) Object detection (b) Image segmentation

FIGURE 6. Examples of (a) an image detection algorithm, YOLOv3 [179] with Darknet, which detects a boat with 91% confidence, and (b) a water segmentation output [180].

step. Two-stage detectors have high localization and object recognition accuracy, while the one-stage detectors achieve high inference speed. A survey of deep learning based object detection [197] has been published recently.

Object detection tasks require high computing power and memory for real-time applications. Therefore, cloud computing [198] or small-sized object detection methods have been used for UAV applications [199]–[202]. Cloud computing assists the system with high computing power and memory. However, communicating with a cloud server brings unpredictable delay from the network. In [198], authors used cloud computing for object detection while keeping low-level object detection and navigation on the UAV.

Another option is to rely on specific object detection models [199]–[202], designed for limited computational power and memory. The papers proposed new object detection models, by using old detection models as their base structure and scaling the original network by reducing the number of filters or changing the layers and they achieved comparable detection accuracy besides the speed on real-time applications on drones. In [201], authors observed a slight decrease on the accuracy while the new network was faster comparing to the old structure. In [203], an adaptive submodularity and deep learning-based spatial search method for detecting humans with UAV in a 3D environment was proposed.

C. FAST AND COMPUTATIONALLY LIGHT METHODS

As mentioned before, some solutions can be rather slow and computationally heavy, but in SAR operations it is vital that the used algorithms are as real-time as possible while still working with high level of confidence. The faster the algorithm can work, the faster the agent can search the area and that probably could lead to faster rescue of the persons in distress. Also the high confidence assures that no important information is missed.

You only look once (YOLO) is the state-of-the-art, real-time object detection system, and YOLOv3 [179] is stated to be extremely fast and accurate compared to methods like R-CNN [204] and Fast R-CNN [205]. An example of the YOLOv3 output is shown in Fig. 6a.

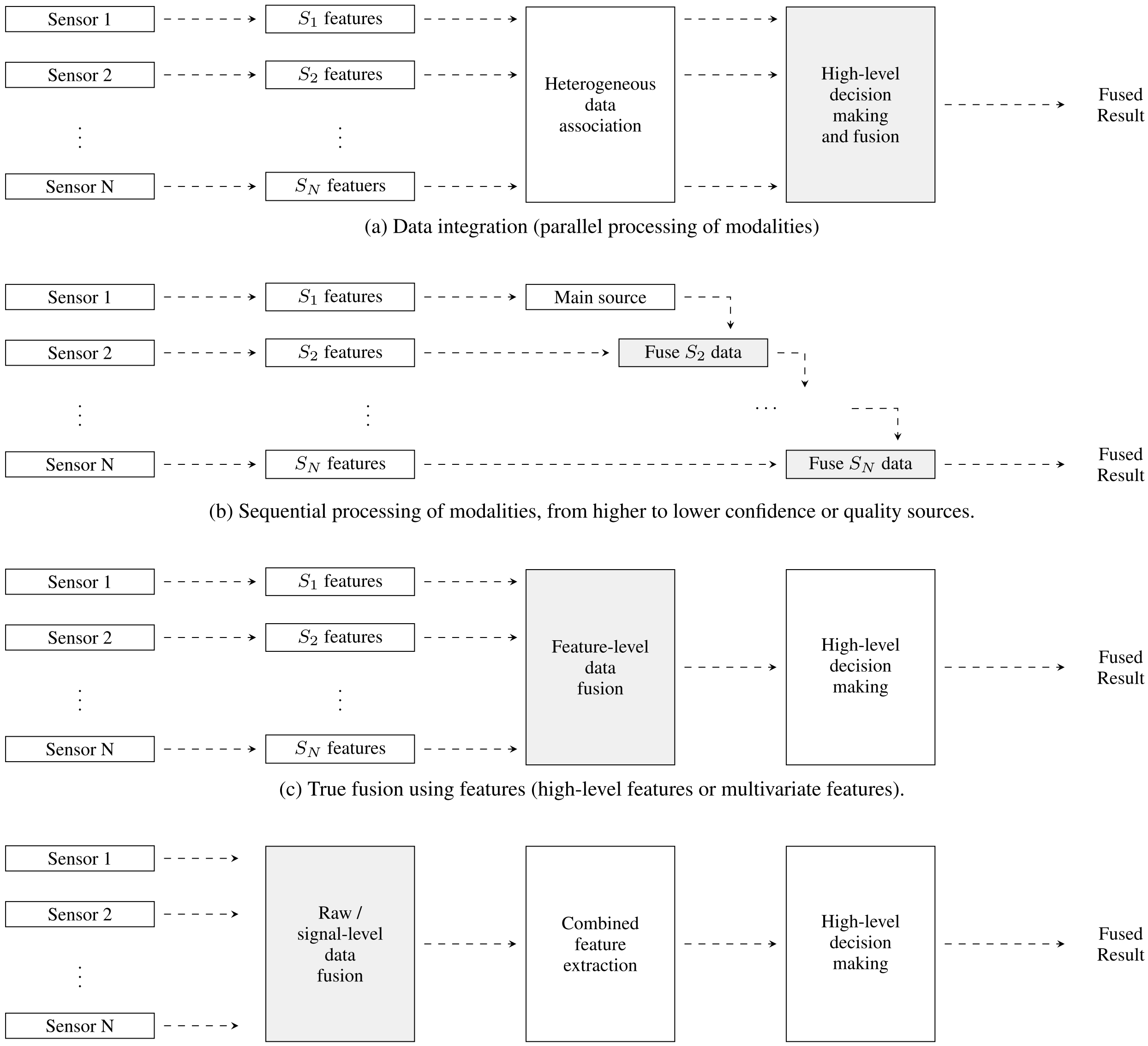
There is active research on methods that can produce more compact networks with improved prediction capability. Common approaches include knowledge distillation [206], where a compact student network is trained to mimic a larger network, e.g., by guiding the network to produce similar activations for similar inputs, and advanced network models, such as Operational Neural Networks [207], where the linear operators of CNNs are replaced by various (non-)linear operations, which allows to produce complex outputs which much fewer parameters.

D. MULTI-MODAL INFORMATION FUSION

Multi-modal information fusion aims at combining data from a multiple sources, e.g., images and LiDAR. Information fusion techniques have been actively researched for decades and there is a myriad of different ways to approach the problem. The approaches can be roughly divided into techniques fusing information on raw data/input level, on feature/intermediate level, or on decision/output level [210]. An overview of the main data fusion approaches in multi-modal scenarios is illustrated in Fig. 7.

Some of the main challenges include *representation*, i.e., how to represent multi-modal data taking into account complementarity and redundancy of multiple modalities, *translation*, i.e., how to map the data from different modalities to a joint space, *alignment*, i.e., how to understand the relations of the elements of data from different modalities, for example, which parts of the data describe the same object in an image and in a point-cloud produced by LiDAR, *fusion*, i.e., how to combine the information to form a prediction, and *co-learning*, i.e., how to transfer knowledge between the modalities, which may be needed, for example, when one the modalities is not properly annotated [211]. The main challenges related to multi-modal data are listed in Table 4.

In research years, also the information fusion techniques have focused more and more on big data and deep learning. Typical deep learning data fusion techniques have some layers specific to each data source and the features can be then combined before the final layers or processed separately all the way to the network output, while the representations



(a) Data integration (parallel processing of modalities)

(b) Sequential processing of modalities, from higher to lower confidence or quality sources.

(c) True fusion using features (high-level features or multivariate features).

(d) True fusion with minimal reduction.

FIGURE 7. Different multi-modal data fusion approaches: (a) parallel data integration with high-level decision making, (b) sequential processing of modalities when different modalities have difference confícende or quality levels, (c) true fusion with high-level features or with multivariate features, and (d) true fusion with minimal reduction [208], [209]. In gray, we highlight the stage in which the fusion happens.

are coordinated through a constraint such as a similarity distance [211], [212].

In SAR operations, the most relevant data fusion applications concern images and depth information [213], [214]. A recent deep learning based approach uses the initial image-based object detection results are to extract the corresponding depth information [214] and, thus, fuses the modalities on the output level. Another recent work proposed a multi-scale multi-path fusion network with that follows a two-stream fusion architecture with cross-modal interactions in multiple layers for coordinated representations [213]. Simultaneous localization and mapping (SLAM) aims at constructing or updating a map of the environment of an agent, while simultaneously keeping track of the agent's position. In SLAM, RGB-D data is used to build a dense 3D map and the data fusion technique applied in a single-agent SLAM is typically extended Kalman Filter (EKF) [215]. Fusing RGB and thermal image data can be needed, for example, in man overboard situations [216]. Typically, there is much less training data available for thermal images and, therefore, domain adaption between RGB and thermal images may help [217].

E. MULTI-AGENT PERCEPTION

To get the full benefit of the multi-robot approach in SAR operations, there should be also information fusion between the agents. For example, an object seen from two different angles can be recognized with a higher accuracy. The sensors carried by different robots may be the same, typically cameras, or different as the presence of multiple agents makes it possible to distribute some of the sensors' weight between the agents, which is important especially in UAV applications. The goal is that the perception the agents have of their environment is based on aggregating information from multiple sources and the agents share information steadily between themselves or to a control station.

The challenges and approaches are similar to those discussed in Section V-D for multi-modal information fusion, but the situation is further complicated by the fact that the data to be fused is located in different physical locations and the sensors are now moving with respect to each other. Some of the challenges that need to be solved are where to perform data fusion, how to evaluate whether different agents are observing the same objects or not, or how to rank observations from different agents. For many of the challenges, there are no efficient solutions yet.

There are several works concentrating on target tracking by multiple agents. These can be divided into four main categories: 1) Cooperative Tracking (CT), which aims tracking moving objects, 2) cooperative multi-robot observation of multiple moving targets (CMOMMTs), where the goal is to increase the total time of observation for all targets, 3) cooperative search, acquisition, and tracking (CSAT), which alternates between the searching and tracking of moving targets, and 4) multi-robot pursuit evasion (MPE) [218], [219]. In SAR operations, especially CSAT approaches can be important after the victims have been initially located, for example, in marine SAR operations, where the victims are floating in the water. For initial search of the victims, a simulated cooperative approach using scanning laser range finders was proposed in [220], but multi-view image fusion techniques for SAR operations are not yet operational.

VI. CLOSING THE LOOP: ACTIVE PERCEPTION IN MULTI-ROBOT SYSTEMS

While we above discussed coverage planning, formation control, and perception aspects of SAR as separate operations, it is obvious that all the components need to function seamlessly together in order achieve optimal performance. This means that coverage planning and formation control need to be adjusted based on the observations and the perception algorithms need to be optimized to support and take full advantage of overall adaptive multi-agent systems. This can be achieved via active perception techniques [221], [222]. While the passive perception techniques simply utilize whatever inputs they are given, active perception methods adapt the behavior of the agent(s) in order to obtain better inputs.

Active perception has been defined as:

> An agent is an active perceiver if it knows *why* it wishes to sense, and then chooses *what* to perceive, and determines *how*, *when*, and *where* to achieve that perception. [223]

In the case of searching a victim, this can mean that the robots are aware that the main purpose is to save humans (why), and are able adapt their actions to achieve better sightings of people in need of help (what) by, for example, zooming the camera to a potential observation (how) or by moving to a position that allows a better view (where and when).

In a SAR operation, active perception can help in multiple subtasks in the search for victims, such as path finding in complex environments [224], obstacle avoidance [225], or target detection [226]. Once a victim has been detected, it is also important to keep following him/her. For instance, in maritime SAR operations, there is a high probability that the survivors are floating in the sea and drifting due to the wind or marine currents. In such scenarios, it is essential that the robots are able to continuously update the position of survivors so that path planning for the rescue vessel can be re-optimized and recalculated in real-time in an autonomous manner. This requires active tracking of the target [227].

While our main interest lies in active perception for multi-robot SAR operations, the literature directly focusing on this specific field is still scarce. Nevertheless, active perception is a rapidly developing research topic and we believe that it will be one of the key elements also in the future research on multi-robot SAR operations. Therefore, we start by introducing the main ideas presented in single-agent active perception and then turn our attention on works that consider active perception in formation control and multi-robot planning. The essence of active perception is understanding, adapting to changes in the environment and taking action for the next mission step.

A. SINGLE-AGENT ACTIVE PERCEPTION

Besides performing their main task (e.g., object detection), active perception algorithms use the same input data to predict the the next action that can help them to improve their performance. This is a challenge for training data collection, because typically there is high number of possible actions in any given situation and it is not always straightforward to decide which actions would be good or bad. A benchmark dataset [228] provides 9000 real indoor input images along with the information showing what would be seen next if a specific action is carried out when a specific image is seen. Another possibility is to create simulated training environments [229], where actions can be taken in a more natural manner. With such simulators, it is critical that the simulator is realistic enough so that employment in the real world is possible. To facilitate the transition, *Sim2Real* learning methods can be used [230]. Finally, it is also possible to use real equipment and environments [224], [231], but such training is slow and requires having access to suitable equipment. Therefore, training setups are typically simplistic. Furthermore, real-world training makes it more complicated to compare different approaches.

Currently, the most active research direction in active perception is reinforcement learning [222]. Instead of learning from labeled input-output pairs, reinforcement learning is based on rewards and punishment given to the agents based on their actions. While reinforcement learning is expected to be the future direction is active perception, its applicability in SAR operations is reduced by the problems of collecting or creating sufficient training data and experiences. Therefore, simpler approaches that use deep neural networks only for

TABLE 4. Main challenges in multi-modal and multi-source data fusion.

Challenge	Description
Noisy data	Different data sources suffer from different types and magnitudes of noise. A heterogeneous set of data sources naturally comes with heterogeneous sources of noise, from calibration errors to thermal noise.
Unbalanced data	Having different data sources often involves data with different characteristics in terms of quality and confidence, but also in terms of spatial and temporal resolution.
Conflicting data	Data from different sources might yield conflicting features. For example, in the case of autonomous robots, different types of sensors (visual sensors, laser rangefinders or radars) might detect obstacles at different distances. Missing data over a certain time interval from one of the sources might also affect the data fusion.

visual data analysis but use traditional approaches, such as proportional-integral-derivative (PID) controllers [232], for control may be currently easier to implement. A way to use active perception in a simulated setting of searching a lost child indoors using a single UAV is described in [226].

B. PERCEPTION FEEDBACK IN MULTI-ROBOT PLANNING AND MULTI-ROBOT SEARCH

Other works in cooperative active tracking and cooperative active localization, have been presented without necessarily considering spatial coordination of fixed formations among the collaborative robots. In [233], active perception was incorporated in a collaborative multi-robot tracking application by planning the paths to minimize the uncertainty in the location of both each individual robot and the target. The robots were UAVs equipped with lidar sensors. In [234], the authors extend the previous work towards incorporating the dynamics of the UAVs in the position estimators with perform real-world experiments. In this second work, a hierarchical control approach was utilized to generate the paths for the different robots.

An extensive description of methods for (i) localization of a stationary target with one and many robots, (ii) active localization of clusters of targets, (iii) guaranteed localization of multiple targets, and (iv) tracking adversarial targets, is presented in [235]. The different methods incorporate both active perception and active localization approaches, and they are mainly focused at ranging measurements based on wireless signals. In terms of SAR robotics and the different systems described in this survey, these type of methods have the most potential in avalanche events for locating ATs, or in other scenarios if the victims have known devices emitting some sort of wireless signal.

In the area of multi-robot search, Acevedo *et al.* recently presented a cooperative multi-robot search algorithm based on a particle filter and active perception [236]. The approach presented in that paper can be exported to SAR scenarios, as the authors focus on optimizing the collaborative search by actively maximizing the information that robots acquire of the search area. One of the most significant contributions within the scope of this survey is that the authors work on the assumption of uncertainty in the data, and therefore propose the particle filter for active collaborative perception. This results in a dynamic reallocation of the robots to different search areas. The system, while mostly distributed, requires the robots to communicate with each other to maintain a common copy of the particle filter. The authors claim that future works will be directed towards further decentralizing the algorithms by enabling asynchronous communication and local particle filters at each of the robots.

In between the areas of multi-robot active coverage and active tracking and localization, Tokekat and Vander *et al.* have presented methods for localizing and monitoring radio-tagged invasive fish with an autonomous USV [237], [238]. Other authors have presented methods for actively acquiring information about the environment. For instance, a significant work in this area that has direct application to the initial assessment and posterior monitoring of the area in SAR scenarios is [239], where the authors present a decentralized multi-robot simultaneous localization and mapping (SLAM) algorithm. The authors identified that optimal path planning algorithms maximizing active perception had a computational complexity that would grow exponentially with both the number of sensors and the planning horizon. To address this issue, they proposed an approximation algorithm and a decentralized implementation with only linear complexity demonstrated with a multi-robot SLAM experiment.

A work on the combination of cooperative tracking together with formation control algorithms for multi-robot systems was introduced in [240]. The authors proposed a perception-driven formation control algorithms that aimed at maximizing the performance of multi-robot collaborative perception of a tracked subject through a non-linear model predictive control (MPC) strategy.

In a similar research direction, Tallamraju *et al.* described in a recent work a formation control algorithm for active multi-UAV tracking based on MPC [241]. One of the main novelties of this work is that the MPC is built from decoupling the minimization of the tracking error (distance from the UAVs to the person) and the minimization of the formation error (constraints on the relative bearing of the UAVs with respect to the tracked person). Another key novelty is that the authors incorporated collision avoidance within the main control loop, avoiding non-convexity in the optimization problem by calculating first the collision avoidance constraints and adding them as control inputs to the MPC formulation.

In more practical terms, the results of [241] enable online calculation of collision-free path planning while tracking a movable subject and maintaining a certain formation configuration around the tracked subject, optimizing the estimation of the object's position during tracking and maintaining it close to the center of the field of view of each of the robots deployed for collaborative tracking. Compared to other recent works, the authors are able to obtain the best accuracy in the estimation of the tracked person's position, while only trading off a negligible increase in error of the self-localization estimation of each of the tracking robots.

A more general approach to collaborative active sensing was presented in [242], where the authors proposed a method for planning multi-robot trajectories. This approach could be applied to different tasks including active mapping with both static and dynamic targets, or for mapping environments with obstacles.

VII. DISCUSSION AND OPEN RESEARCH QUESTIONS

Research efforts have mainly focused on the design of individual robots autonomously operating in emergency scenarios, such as those presented in the European Robotics League Emergency Tournament. Most of the existing literature in multi-robot systems for SAR either relies on an external control center for route planning and monitoring, on a static base station and predefined patterns for finding objectives, or have predefined interactions between different robotic units. Therefore, there is a big potential to be unlocked throughout a wider adoption of distributed multi-robot systems. Key advances will require embedding more intelligence in the robots with lightweight deep learning perception models, the design and development of novel distributed control techniques, and a closer integration of perception and control algorithms. Moreover, heterogeneous multi-robot systems have shown significant benefits when compared to homogeneous systems. In that area, nonetheless, further research needs to focus on interoperability and ad-hoc deployments of multi-robot systems.

Based on the different aspects of multi-robot SAR that have been described in this survey, both at the system level and from the coordination and perception perspectives, we have summarized the main research directions where we see the greatest potential. Further development in these areas is required to advance towards a wider adoption of multi-robot SAR systems.

A. SHARED AUTONOMY

With the increasing adoption of multi-robot systems for SAR operations over individual and complex robots, the number of degrees of freedom that can be controlled has risen dramatically. To enable efficient SAR support from these systems without the need for a large number of SAR personnel controlling or supervising the robots, the concept of shared autonomy needs to be further explored.

The applications of more efficient shared autonomy and control interfaces are multiple. For instance, groups of UAVs flying in different formation configurations could provide real-time imagery and other sensor information from a large area after merging the data from all the units. In that scenario, the SAR personnel controlling the multi-UAV system would only need to specify the formation configuration and control the whole system as a single UAV would be controlled in a more traditional setting.

While some of the directions towards designing control interfaces for scalable homogeneous multi-robot systems are relatively clear, further research needs to be carried out in terms of conceptualization and design of interfaces for controlling heterogeneous robots. These include land-air systems (UGV+UAV), sea-land systems (USV+UAV), and also surface-underwater systems (USV+UUV), among other possibilities. In these cases, owing to the variability of their operational capabilities and significant differences in the robots dynamics and degrees of freedom, a shared autonomy strategy is not straightforward.

B. OPERATIONAL ENVIRONMENTS

Some of the main open research questions and opportunities that we see for each of the scenarios described in this paper in terms of deployment of multi-robot SAR systems are the following:

- Urban SAR: we have described the various types of ground robots being utilized in USAR scenarios and collaborative UGV+UAV systems. In this area, we see the main opportunities and open challenges to be in (i) collaborative localization in GNSS denied environments; (ii) collaborative perception of victims from different perspectives; (iii) ability to perform remote triage and establish a communication link between SAR personnel and victims, or to transport medicines and food; and (iv) more scalable heterogeneous systems with various sizes of robots (both UGVs and UAVs) capable to collaboratively mapping and monitoring harsh environments or post-disaster scenarios.
- Marine SAR: throughout this survey, we have seen that marine SAR operations are one of the scenarios where heterogeneous multi-robot systems have been most widely adopted. Nonetheless, there are multiple challenges remaining in terms of interoperability and deployability. In particular, few works have explored the potential in closely designing perception and control strategies for collaborative multi-robot systems including underwater, surface and aerial robots [243]. Moreover, while the degree of autonomy of UAVs and UUVs has advanced considerably in recent years, USVs can benefit from the data gathered by these to increase their autonomy. In terms of deployability, more robust solutions are needed for autonomous take-off and docking of UAVs or UUVs from surface robots. Finally, owing to the large areas in which search for victims takes place in maritime SAR operations, active perception approaches increasing the efficiency of search tasks have the most potential in these environments.
- Wilderness SAR: some of the most important challenges in WiSAR operations are the potentially remote and unexplored environments posing challenges to both communication and perception. Therefore, an essential

step towards more efficient multi-robot operations in WiSAR scenarios is to increase the level of autonomy and the operational time of the robots. Long-term autonomy and embedded intelligence on the robots for decision-making without human supervision are some of the key research directions in this area in terms of multi-robot systems.

C. SIM-TO-REAL METHODS FOR DEEP LEARNING

Deep-learning-based methods are flexible and can be adapted to a wide variety of applications and scenarios. Good performance, however, comes at the cost of enough training data and an efficient training process that is carried out offline. Other deep learning methods, and particularly deep reinforcement learning (DRL), rely heavily on simulation environments for converging towards working control policies or stable inference, with training happening on a trial-and-error basis. Search and rescue robots are meant to be deployed in real scenarios where the conditions can be more challenging than those of more traditional robots. Therefore, an important aspect to take into account is the transferability of the models trained in simulation to the reality.

Recent years have seen an increasing research interest in closing the gap between simulation and reality in DRL [244]. In the field of SAR robotics, a relevant example of the utilization of both DL and DRL techniques was presented by Sampedro *et al.* [245]. The authors developed a fully autonomous aerial robot for USAR operations in which a CNN was trained to for target-background segmentation, while reinforcement learning was utilized for vision-based control methods. Most of the training happened with a Gazebo simulation and ROS, and the method was tested also in real indoor cluttered environments. In general, and compared with other DL methods, DRL has the advantage in that it can be used to provide an end-to-end model from sensing to actuation, therefore integrating the perception and control aspects within a single model. Other recent applications of DRL for SAR robotics include the work of Niroui *et al.* [246], with an approach to navigation in complex and unknown USAR cluttered environments that used DRL for frontier exploration. In this case, the authors put an emphasis on the efficiency of the simulation-to-reality transfer. Another recent work by Li *et al.* [247] showed the versatility of DRL for autonomous exploration and the ability of transferring the model from simulation to reality in unknown environments. We discuss the role of DRL in active perception in Section VI. Bridging the gap between simulation and reality is thus another challenge in some of the current SAR robotic systems.

D. HUMAN CONDITION AWARENESS AND TRIAGE

As we have discussed in multiple occasions throughout this survey, the current applicability of SAR robotics is mainly in the search of victims or the assessment and monitoring of the area by autonomously mapping and analyzing the accident or disaster scenario. However, only a relatively small amount of works in multi-robot SAR robotics have been paying attention to the development of methods for increasing the awareness of the status of the victims in the area or performing remote triage.

The potential for lifesaving applications in this area is significant. The design and development of methods for robots to be able to better understand the conditions of survivors after an accident is therefore a research topic with multiple open questions and challenges. Nonetheless, it is important to take into account that this most likely requires the robots to reach to the victims or navigate near them. The control of the robot and its awareness of its localization and environment thus need to be very accurate, as otherwise operating in such safety-critical scenario might be counterproductive. Therefore, before being able to deploy in a real scenario novel techniques for human condition awareness and remote triage, the robustness of navigation and localization methods in such environments needs to be significantly streamlined.

E. HETEROGENEOUS MULTI-ROBOT SYSTEMS

Across the different types of SAR missions that have been discussed in this survey, the literature regarding the utilization of heterogeneous robots has shown the clear benefits of combining either different types of sensors, different perspectives, or different computational or operational capabilities. Nonetheless, most of the existing literature assumes that the identity and nature of the robots and the way in which they communicate and share data is known a priori. A wider adoption and deployment of heterogeneous multi-robot systems therefore needs research to advance in the following practical areas:

- Interoperability: flexible deployment of a variable type and number of robots for SAR missions requires the collaborative methods to be designed with wider interoperability in mind. Interoperability has been the focus of both the ICARUS and DARIUS projects [30], [49]. Moreover, extensive research has been carried out in interoperable communication systems, and current robotic middlewares, such as ROS2 [248], enable distributed robotic systems to share data and instructions with standard data types. Nonetheless, there is still a lack of interoperability in terms of high-level planning and coordination for specific missions. In SAR robotics, these include collaborative search and collaborative mapping and perception.
- Ad-hoc systems: closely related to the concept of interoperability in terms of high-level planning, wider adoption of multi-robot SAR systems requires these systems to be deployed in an ad-hoc manner, where the type or number of robots does not need to be predefined. This has been explored, to some extent, in works utilizing online planning strategies that account for the possibility of malfunctioning or missing robots [119].
- Situational awareness and awareness of other robots: the wide variety of robots being utilized in SAR missions, and the different scenarios in which they can be applied, calls for the abstraction and definition of models

defining these scenarios but also the way in which robots can operate with them. In heterogeneous multi-robot systems, distributed high-level collaborative planning requires robots to understand not only how can they operate in their current environment and what are the main limitations or constraints, but also those conditions of different robots operating in the same environment. For instance, a USV collaborating with other USVs and UAVs in a maritime SAR mission needs to be aware of the different perspectives that UAVs can bring into the scene, but also of their limitations in terms of operational time or weather conditions.

F. ACTIVE PERCEPTION

We have closed this survey exploring the literature in active perception for multi-robot systems, where we have seen a clear lack of research within the SAR robotics domain. Current approaches for area coverage in SAR missions, for instance, mostly consider an a priori partition of the area among the available robots. Dynamic or online area partitioning algorithms are only considered either in the presence of obstacles, or when the number of robots changes [119]. Other works also consider an a priori estimation of the probability of locating victims across different areas to optimize the path planning [142], [143]. These and other works are all based in either a priori-knowledge of the area, or otherwise partition the search space in a mostly homogeneous manner. Therefore, there is an evident need for more efficient multi-robot search strategies

Active perception can be merged into current multi-robot SAR systems in multiple directions: actively updating and estimating the probabilities of victims' locations, but also with active SLAM techniques by identifying the most severely affected areas in post-disaster scenarios. In wilderness and maritime search and rescue where tracking of the victims might be necessary even after they have been found, active perception has the potential to significantly decrease the probability of missing a target.

In general, we also see the potential of active perception within the concepts of human-robot and human-swarm cooperation, and in terms of increasing the awareness that robots have of victims' conditions. Regarding human-robot and human-swarm cooperation, active perception can bring important advantages in the understanding the actions of SAR personnel and being able to provide more relevant support during the missions.

VIII. CONCLUSION

Among the different civil applications where multi-robot systems can be deployed, search and rescue (SAR) operations are one of the fields where the impact can be most significant. In this survey, we have reviewed the status of SAR robotics with a special focus on multi-robot SAR systems. While SAR robots have been a topic of increasing research attention for over two decades, the design and deployment of multi-robot systems for real-world SAR missions has only been effective more recently. Multiple challenges remain at the system-level (interoperability, design of more robust robots, and deployment of heterogeneous multi-robot systems, among others), as well as from the algorithmic point of view of multi-agent control and multi-agent perception. This is the first survey, to the best of our knowledge, to analyze these two different points of view complementing the system-level view that other surveys have given. Moreover, this work differentiates from others in its discussion of both heterogeneous systems and active perception techniques that can be applied to multi-robot SAR systems. Finally, we have listed the main open research questions in these directions.

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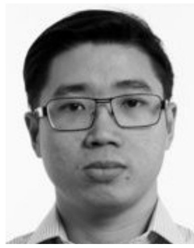

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