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Robots Saving Lives: A Literature Review About Search and Rescue (SAR) in Harsh Environments

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***Abstract*— In recent years, the rise in both natural and man-made disasters, along with armed conflicts and terrorist threats, has elevated the demand for Search and Rescue (SAR) missions worldwide. This paper underscores the critical necessity to enhance SAR capacity, safety, and capabilities, with a primary goal of reducing response times through the integration of robots into SAR operations. The examination of research on robotized SAR highlights deficiencies in both software and hardware, particularly focusing on perception systems for robotized SAR platforms.**

I. Introduction

Recent years have seen an increase in the number of both man-made and natural disasters. Every year around 400 natural disasters are expected to happen around the world. Alongside natural disasters, there are 30–40 active armed conflicts at any time [1]. Furthermore, there is an ever-present threat of terrorist attacks, as well as an increased number of lost or missing people [2]. This increased number of disasters and subsequent number of Search and Rescue (SAR) operations leads to an increase in the workload of SAR teams around the world. Since the ultimate goal of any SAR operation is to save the lives of affected people, any way of increasing the capacity, safety, and capabilities of SAR teams, as well as reducing their response time, is of paramount importance. One of the main ways to accomplish these goals is to use robots in SAR operations.

Over the previous years, SAR robots have already been used, and their adoption, as well as their capabilities, are continuously increasing. One of the first instances of SAR robot deployment was during the World Trade Center (WTC) collapse in 2001 [3]. Ever since then, SAR robots have been deployed in most natural and man-made disaster scenarios, most notably during the Fukushima nuclear power plant disaster in Japan [4]. With the rapid advancement in technologies required by the SAR operations, thus the SAR robots as well, we are expecting to see an increase in the number and scope of the automated SAR missions.

The field of SAR has garnered interest and has led to the emergence of many survey studies. The chapter Search and Rescue Robotics in [5] covers how disasters impact the design of rescue robots, the sorts of robots deployed, their assessment, and the problems and future of these robots, with an emphasis on disaster rescue. Similarly, Schneider and Wildermuth evaluated the performance of Unmanned Ground Vehicles (UGVs) and Unmanned Aerial Vehicles (UAVs) in disaster response activities. Their work outlines specific requirements for SAR, including navigation, mapping, and casualty identification, and presents innovative hardware designs for SAR robots [6].

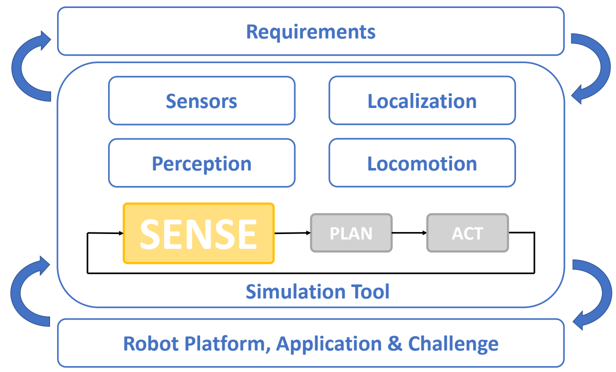

Fig. 1: Overview of our survey paper.

Moreover, Bogue examined the prospects of robots in disaster relief and search and rescue operations, with a specific emphasis on addressing user requirements and prioritizing development efforts. The identification of key user requirements and development goals for aerial, ground, and marine robots has been accomplished in his work, which directs research and development efforts for SAR [7]. Most recently, a survey about simulation tools for Urban Search and Rescue (USAR) in presented in [8]. Despite significant interest in surveying SAR, earlier work does not give an overview of SAR software development, particularly state-of-the-art perception and localization systems. In addition, an in-depth assessment of what is required and what is a restriction in terms of hardware and software for UGVs and UAVs is inadequate.

Our primary contribution fills the existing gap by presenting a comprehensive state-of-the-art survey of the requirements, hardware, software, and platforms crucial for SAR operations, as depicted in Fig. 1. Additionally, we provide an in-depth analysis of sensors and perception algorithms specifically tailored for SAR applications, topics that have been notably underexplored in previous literature.

The structure of this paper is organized as follows: Section II introduces the requirements for hardware and software utilized in SAR robots. The specific hardware and software

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components are detailed in Section III. Finally, Section IV provides the conclusion and offers insights into future directions for SAR research.

II. Requirements

SAR robots need to operate in some of the harshest and most challenging environments in the world. On top of that, their main task is the rescue of injured, trapped or lost people, making the allowed error margin extremely slim. Considering this, the requirements for UAVs and UGVs used in SAR operations are very strict. According to Schneider and Wildermuth [6] SAR robot requirements can be divided into three main categories: Search-specific, Rescue-specific, and General requirements. Search-specific requirements include all the requirements regarding navigation and mapping, as well as casualty identification. All communication, casualty support, and remote mobile manipulation requirements are grouped under Rescue-specific requirements. Finally, time of operation (battery life), user interface, safety, and portability requirements are all grouped under General requirements. Due to the scope of this paper, we are mainly focusing on the Search-specific group of requirements.

To achieve navigation and mapping, as well as survivor identification goals, different sensing and perception techniques and technologies need to be utilized. No matter which combination of sensors and perception algorithms is used, it needs to be able to provide accurate, complete and timely information to the robot or the operator for decision-making. Furthermore, redundancy in sensors and perception algorithms is desired, due to the harsh environments of operation, which make the chance of equipment failure or unsuitability greater. According to Bogue [7], SAR perception systems need to complete the following tasks: Obstacle detection, Rapid image analysis, Indoor and outdoor Operation, and Operation in vision-obscured environments. Furthermore, the SAR robot in general needs to be able to avoid collisions, achieve adequate operation times, be able to operate in collapsed buildings or underground, operate while being exposed to hazardous chemicals, radiation levels, etc., and have sufficient dust and moisture protection. The communication aspect of the SAR robot is also a big topic among the requirements. Generally, it can not be assumed that communication with the robot will be possible throughout the entire mission, so at least a certain degree of autonomy is required. Depending on the application field, a single SAR robot does not need to fulfil all requirements.

III. Hardware and Software for Search and Rescue

A. Sense-Plan-Act

In robotics, paradigms are built on three widely accepted essential elements: SENSE, PLAN, and ACT (see Fig. 1) [9]. These three classes can also be applied to robot software. If a function involves obtaining data about the environment using sensors and developing a representation of the world for other operations, it falls under the SENSE category. If a function gets the previously defined world model and provides one or more action plans for the robot to perform, it is classified as a PLAN function. The ACT generates actuator instructions based on planning stage instructions. This design paradigm has been applied in SAR robots as well, but Sense-Plan-Act might be merged [2], [10]. As already briefly mentioned in the introduction, the focus of this paper is on the sensors, algorithms, and software linked to the SENSE part. However, the PLAN and ACT parts are also of great importance and are topics that deserve their own separate analysis due to the sheer scope they cover.

B. Sensors

In order to fulfil all their missions successfully, SAR robots are equipped with a plethora of different sensors, ranging from the simplest odometry sensors to complex cameras and Radars. We divide all these sensors into two different categories: **localization** sensors and **perception** sensors. Table I gives an overview of all the sensor types mentioned, alongside with the sources.

1) Localization Sensors: are sensors used purely for localising the robot in space. Their main task is to provide an accurate position (relative or absolute) of the robot. This position information is essential for navigation, path planning, and rescue action planning and execution. These sensors function based on different technologies and techniques. In SAR applications, due to complex and dynamic environments, it is needed to have robust and redundant localization.

Global navigation satellite system (GNSS) sensors rely on communication with different satellites and triangulation of signals from those satellites to determine the absolute position of the robot. GNSS sensors are the most common sensors used for localization, not only in SAR robots, but in general. There are different navigation satellite systems including GPS, Galileo (EGNSS), GLONASS, BDS (BeiDou), QZSS, as well as others. GNSS receivers can utilize one or more of the aforementioned satellite systems. Although GNSS sensors are very precise, with maximum accuracies in the centimeter range, their major limitation is the required clear line of sight for communication with the satellites, limiting their usage to outdoor environments. They are also quite susceptible to reflected signals, a phenomenon known as the multi-path problem.

Wheel odometry sensors utilize rotary encoders to quantify wheel rotations, facilitating the conversion of this information into positional and velocity data. Despite its accuracy in the short term, the method is prone to error accumulation over time, particularly due to issues such as wheel slippage and friction. Additionally, the determination of orientation necessitates an alternative measurement method or a calculation based on both wheel rotation and distance covered. It is important to note that this technology is applicable solely to tracked and wheeled UGVs and is not suitable for UAVs. These sensors are employed in SAR robots as a redundant measure when GNSS sensors fail to provide precise and accurate location information.

The **Inertial Measurement Unit (IMU)**, encompassing an Accelerometer, a Magnetometer, and a Gyroscope, is pivotal for determining a robot's heading, attitude, and position. However, susceptibility to interference from electronics and the robot's structure poses challenges for accurate readings, making IMUs less viable for prolonged usage. Addressing these challenges requires careful engineering considerations for IMU quality to enhance long-term reliability in diverse operational scenarios. In conjunction with the IMU, the Inertial Navigation System (INS) serves as a comprehensive solution for autonomous robot guidance. The IMU captures linear accelerations and angular rates, while the INS, powered by advanced algorithms including Kalman filtering, processes this data to continuously compute the robot's position, velocity, and orientation. This self-contained navigation system is particularly advantageous in SAR scenarios where external signals like GNSS are unreliable or unavailable, ensuring continuous operation and high accuracy over short to medium distances.

2) Perception Sensors: Perception sensors are devices that gather information from the environment to enhance awareness and understanding. These sensors are employed in SAR robots to collect data about the surroundings. The information collected by perception sensors aids in decision-making processes, allowing systems to respond effectively to changing conditions or stimuli.

Light Detection and Ranging (Lidar), harnessing Infrared (IR) lasers as a light source, presents a promising avenue for achieving robust perception across diverse environments and weather conditions, including potential underwater applications. This technology, known for its high resolution and cost-effectiveness, encounters challenges related to reduced precision in fog and heavy rain, along with susceptibility to lens contamination. Exploring improvements like the integration of flash Lidar technology and the adoption of solid-state Lidars is crucial for overcoming these obstacles and ensuring consistent and reliable performance. The feasibility of attaining a full 360° Horizontal Field of View (HFoV) coverage with a singular sensor streamlines practical implementation, contributing to the continual evolution of iidar systems based on IR laser technology.

Radio Detection and Ranging (Radar), despite its lower resolution, plays a crucial role in SAR applications due to its adaptability in diverse conditions and extended detection range, making it essential for effective remote sensing. In challenging scenarios, Radar demonstrates reliability and reduced sensitivity to environmental factors like interference or topographic variations. The trade-off between resolution and detection range highlights Radar's significance in providing vital information for SAR applications.

Cameras play a pivotal role in achieving comprehensive environmental perception for SAR robots. One approach involves the utilization of RGB-D cameras employing stereo depth measurement. A single 360° HFoV camera is characterized by lower complexity and implementation difficulty but is constrained to a 20m range and daylight operation. Alternatively, a multi-camera setup, albeit more intricate due to point cloud fusion, offers a complete 360° HFoV, with some models theoretically providing an infinite depth range. However, nocturnal limitations prompt the suggestion of augmenting these systems with thermal cameras or infrared (IR) coupled with distance measuring systems. Additionally, thermal cameras, recognized for their passive operation and all-weather functionality, require multiple units owing to their limited HFoV. Meanwhile, the Depth Time of Flight (ToF) camera, functioning akin to Lidar but at a lower cost with greater resistance to ambient light, is considered for redundancy or close-range object detection. Lastly, the RGB-D camera employing ToF depth measurement combines ToF sensors with RGB cameras to generate point clouds, necessitating multiple sensors for a complete 360° HFoV. These camera configurations collectively address challenges related to range, accuracy, environmental conditions, and operational hours in autonomous vehicle perception systems.

Microphone arrays are crucial for sound source localization in various applications. In Search and Rescue robots, these arrays are designed to optimize sensory input for effective audio-based detection. Circular or planar configurations with strategically placed microphones capture sound from different directions. The choice of sensors considers factors like sensitivity, frequency response, and directional characteristics. High-quality microphones with broad frequency ranges are preferred for dynamic environments. Additionally, features like low self-noise enhance the system's ability to detect faint or distant sounds, which is crucial in search and rescue scenarios.

C. Perception

This section delves into how different sensors are employed for perception and recognition, which is crucial for effective and safe operations. These are illustrated in Fig. 2 and will be discussed in the following subsections.

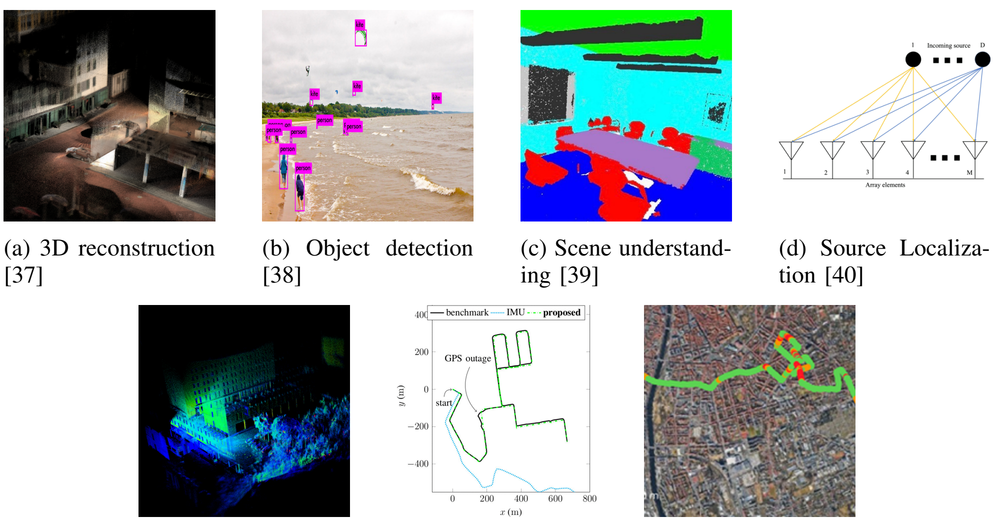
1) 3D Reconstruction: Recent advances in 3D reconstruction, crucial for rescue missions, utilize depth, monocular, and stereo cameras, with Lidar for sparse point clouds, as shown in Fig. 2a. Depth cameras excel indoors but falter outdoors, impacting 3D city mapping in complex outdoor settings where Lidar is essential [37]. 3D map reconstruction with cameras involves a sophisticated algorithmic process [44], [45], differing from real-time SLAM (Simultaneous Localization and Mapping). Offline Lidar reconstruction, unlike SLAM, focuses on data precision and detail, yielding accurate 3D models useful in archaeology, urban planning, and forestry. This method integrates multi-modal data, including high-resolution cameras, thermal imaging, and sometimes ground-penetrating radar, enhancing model depth and accuracy. Machine learning further refines this data, producing comprehensive 3D models with contextual richness.

2) Object Detection and Classification: High-precision 3D maps enable unmanned vehicles and drones to efficiently navigate rescue areas with minimal computing resources, focusing on tasks like object detection. In disaster areas, deploying UAVs and UGVs with advanced detection systems is vital for rescue efforts.

TABLE I: Overview and comparison of sensors used for SAR operations

Sensor	Usage	Range	Price	OR*	Type	Failure and Limiting circumstances	Sources
GNSS	L	N/A	Low	Low	Passive	Obstructions and Signal Blockage, Multipath Interference, Adverse Weather Conditions, Poor Satellite Geometry, Signal Spoofing and Jamming, Electromagnetic Interference	[11], [12]
IMU/INS	L	N/A	Medium	Medium	Passive	Sensor Calibration Issues, Electromagnetic Interference, Temperature Variations, Sensor Cross-Coupling, High Dynamic Conditions, Vibration and Shock	[11], [13], [14], [15], [16]
Mono RGB camera	L & P	Low	Low	Low	Passive	Low Light Conditions, Noisy Environments, Occlusions, High Dynamic Range Scenes, Adverse Weather Conditions, Glossy or Reflective Surfaces, Fast Motion	[17], [18]
Stereo RGB camera	L & P	Low	Medium	Low	Passive	Calibration Issues, Baseline Limitations, Occlusions, Low Light Conditions, Glossy or Reflective Surfaces, Inadequate Disparity Range, Adverse Weather Conditions	[18], [19]
RGB-D camera	L & P	Low	Medium	Low	Active	Low Light Conditions, Occlusions, Smoke, Adverse Weather Conditions, Fast Motion	[18], [19], [20]
Thermal camera	L & P	Low	High	High	Passive	Low temperature variation, Infrared transparency, Weather interference, Reflective surfaces, Distance limitations, Low contrast scenes	[18], [19], [21], [22], [23], [24]
Lidar	L & P	High	High	Medium	Active	Adverse Weather Conditions, Sun Glare, Occlusions, Interference From Other Lidars, Smoke	[18], [19], [25], [26], [27], [28]
Radar	L & P	High	Medium	High	Active	Obstructions or Clutter, Electromagnetic Interference, Occlusions, Unfavourable Terrain, Vibrations	[18], [19], [29], [30], [31]
Microphone array	P	Low	Medium	Medium	Passive	Noise Interference, Reflections and Poor Acoustics, Electronic Interference, Environmental Conditions	[19], [32], [33], [34], [35], [36]

Abbreviations are: Localization (L), Perception (P), Not Applicable (N/A). *Operational robustness (OR) in the sense of the number various environments and applications where the sensor can be effectively used.



(a) 3D reconstruction [37]

(b) Object detection [38]

(c) Scene understanding [39]

(d) Source Localization [40]

(e) SLAM [41]

(f) IMU [42]

(g) GNSS [43]

Fig. 2: Illustration of perception and localization methods.

Deep learning, especially Convolutional Neural Networks (CNNs), is crucial here. Algorithms like Faster R-CNN [46] and YOLO (You Only Look Once) [38] are commonly used for detection, as shown in Fig. 2b. Faster R-CNN identifies potential object locations before classifying them with CNNs, while YOLO predicts object classifications and locations simultaneously, offering faster processing crucial in emergencies. In poor visibility or partially obscured conditions, algorithms like SSD (Single Shot MultiBox Detector) [47] and RetinaNet [48] ensure reliable detection. Integrating these algorithms into UAVs and UGVs creates intelligent systems capable of autonomous navigation and vital information gathering in disaster zones. This technology enhances rescue operation efficiency, enabling quicker responses and better-informed decisions in emergencies.

3) Scene Understanding: 3D scene understanding in computer vision extends beyond object detection to interpret environments, including spatial relationships, hazard identification, and pathway recognition, as shown in Fig. 2c. Segmentation algorithms [49] are essential, dividing the 3D SAR space into coherent parts like buildings, roads, and terrain, aiding in assessing accessibility and safety in disaster zones [50]–[53]. Integrating these algorithms into rescue operations transforms response capabilities. Advanced 3D scene understanding allows drones and robots to autonomously navigate complex terrains, identify safe zones, assess structural stability, and adapt to evolving environments. This enhances rescue safety and efficiency, reduces response time, and ultimately saves lives and mitigates disaster impacts.

4) Sound Source Localization (SSL): Sound source localization (SSL), as shown in Fig. 2d emerges as a critical technology, especially in scenarios where visual cues are obscured or unavailable. SSL enables unmanned systems to pinpoint the location of individuals or key sound-emitting sources solely based on auditory signals. This technology, integrating various techniques such as Direction-of-Arrival (DOA) estimation, distance estimation, and Time Difference of Arrival (TDOA) calculations, significantly enhances the accuracy and reliability of localization in unmanned systems [54]–[58]. The application of SSL in robotics, especially in drones and unmanned vehicles, encompasses advanced methodologies like learning-based approaches using neural networks, beamforming techniques, and particle filtering [59]–[61]. These methods address the challenges of multiple sound sources and mobility of both the robots and the sound sources, thereby facilitating rapid and precise localization in rescue scenarios. However, SSL in complex environments still faces challenges such as noise interference, reverberation effects, and the identification of multiple sound sources [62]–[64]. Future research is directed towards enhancing the robustness and adaptability of SSL systems to cater to the dynamic nature of rescue environments, thereby augmenting the efficiency of rescue operations.

D. Localization

This section focused on how these vehicles use sensor data for precise self-localization and environmental mapping.

1) Simultaneous Localization and Mapping(SLAM): SLAM (Simultaneous Localization and Mapping) algorithms, as shown in Fig. 2e are crucial in rescue operations, enabling unmanned vehicles to navigate and map unknown or dynamic environments.

Visual SLAM (vSLAM), using optical sensors, is key in precision navigation, like moving through collapsed buildings. ORB-SLAM [65], a notable example, uses ORB features for mapping and tracking, adapting to lighting and perspective changes. This provides rescue teams with detailed visual data of the environment.

Lidar-based SLAM, employing laser sensors, excels in creating 3D maps, suitable for outdoor or large-scale disaster environments. LOAM-related works [41], [66] offer high accuracy in localization and mapping, which is crucial for disaster response planning and damage assessment.

Multi-modal SLAM combines various data sources, like cameras, Lidar and GPS. Algorithms like R3lIVE [67] integrate visual SLAM's imagery with Lidar SLAM's depth data, offering a comprehensive environment view. This is particularly effective in challenging conditions, like low-light or varied terrains, ensuring reliable navigation and mapping.

In rescue operations, SLAM algorithms' ability to rapidly generate accurate maps and navigate effectively is life-saving. They allow drones and unmanned vehicles to explore dangerous or inaccessible areas, quickly identifying survivors, assessing structures, and providing critical information, enhancing the effectiveness of rescue efforts.

2) Dead reckoning: (IMU, odometry localization)

Dead Reckoning, as shown in Fig. [68], [69] works by estimating the current position based on a previously determined location, using data about speed and direction of movement2f. This method can be effective when quick and approximate localization is necessary, especially in fast-changing scenarios typical of rescue missions. Dead Reckoning provides a foundation for initial localization and quick navigation decisions [70]. It enables robots to maintain an ongoing estimate of their position, allowing them to traverse unknown or hazardous terrains to locate survivors, deliver supplies, or assess structural integrity in areas where traditional localization methods are ineffective. Furthermore, when Dead Reckoning is integrated with other technologies like SLAM or GPS [71], it forms part of a robust, multi-modal localization system. This integration allows for continuous and accurate tracking of rescue vehicles or drones, ensuring that they can operate effectively in the complex and dynamic environments typical of disaster scenarios.

3) GNSS localization: In the sphere of SAR operations, Global Navigation Satellite Systems (GNSS) [72], which include systems like GPS, GLONASS, Galileo, and BeiDou [73], are integral for precise and reliable localization, as shown in Fig. 2g.

E. Platforms and Locomotion

In the realm of SAR operations, the strategic selection of platforms and their locomotion attributes plays a pivotal role in operational efficacy. Table II offers a systematic comparison of diverse SAR platforms, from aerial UAVs to aquatic Unmanned Surface Vessels (USVs), each classified by mobility type. Evaluated by robotics specialists on crucial performance metrics—Mobility, Stability, Adaptation to the Environment, Energy Efficiency, and Speed and Agility—the platforms are rated on a scale reflecting their effectiveness. This analytical overview is useful for understanding each platform's strengths and limitations, eventually improving life-saving responses in critical situations.

F. Simulation Tools

Simulation tools are crucial in the development of SAR robots, encompassing hardware and software, as they offer a safer, cost-effective, and efficient alternative to real-world trials. They enable researchers to evaluate new concepts without harm and provide prompt error detection, enhancing efficiency in the construction of robotic systems [8].

The table III compares open-source simulation tools for SAR operations, evaluating them across key criteria such as simulation capabilities of harsh environments, environmental factors (rain, smoke, snow, fire, slippery ground, etc.), sensor and robot modeling, out-of-box software, interface quality, and hardware requirements, based on our previous work and projects [77]. ISAAC consistently receives good or very good ratings in all categories. Nonetheless, it has the most stringent hardware requirements. The igniting Gazebo could

TABLE II: Overview and comparison of platforms and locomotion types for SAR operations

Platform	Propulsion type	Locomotion type	MO	ST	OR	OD	SA	Example
UAV	Propeller, Jet	Flying	High	Low	+	Low	+++	DJI Drone
UGV	Tracked, Wheeled	Rolling	Low	High	+++	High	+	THeMIS [74]
Legged robots	Bipedal,Quadrupedal, Hexapod, Octoped, Multi-legged	Walking, Running, Jumping, Climbing	Low	Low	++	Low	++	Unitree Robotics
Humanoid	-	Same as legged robots, manipulating objects	Low	Low	++	Low	++	Tesla Optimus
serpentine robot	-	Crawling, Climbing	Low	High	+++	o	+	OmniTread OT-4 [75]
USV	Propeller	Steaming	Low	High	++	High	++	Guardian [76]

Abbreviations in the first row are: Mobility (MO), Stability (ST), Operational Robustness (OR), Operational Duration (OD), Speed and Agility (SA). The symbols rate the quality of implementation: (o) not rated or irrelevant, (+) ok, (++) good, (+++) very good.

TABLE III: Overview and comparison of open-source simulation tools for SAR, inspired by [77]

Simulator	Group	Visualization	HE	EF	SE	RM	OSW	IF	HWR	License
Carla [78]	AD	UE 4.26	+	++	+++	+	+++	+++	++	MIT & CC-BY*
AirSim [79]	Drone/AD	UE 5.2	++	+++	++	+	++	++	++	MIT
Ignition Gazebo [80]	Robotics	OGRE2	+++	++	++	+++	+++	+++	+	Apache 2.0
ISAAC [81]	Robotics	Omniverse	++	++	+++	+++	++	++	+++	NVIDIA EULA
MuJoCo [82]	RL	OpenGL	++	++	+	+++	+++	++	+	Apache 2.0
Webots [83]	Robotics	OpenGL	+	o	++	+++	+++	+++	+	Apache 2.0
GRID [82]	LLM+Drone	UE 5.2	++	+++	++	+	++	++	++	RAIL-S
ZeroSim [84]	Robotics	Unity 2020.x LTS	o	o	++	+	+	+	+	BSD 2-Clause

Abbreviations in the first row are: Harsh Environments (HE), Environmental Factors (EF), Sensor (SE), Robot Model (RM), Out-of-box Software (OSW), Interface (IF), HWR (Hardware Requirement). The symbols rate the quality of implementation: (o) not rated or irrelevant, (+) ok, (++) good, (+++) very good. *The code of Carla simulator has a MIT license while the assets have a CC-BY license.

be a light alternative with generally good ratings. AirSim, MuJoCo, and GRID are also effective, particularly in modeling environmental conditions and sensors. Carla receives mixed evaluations but provides excellent sensor simulation. Unfortunately, no direct simulation tool is specifically created for SAR research. However, there are several feasible tools for various parts of SAR simulation, each with its own set of capabilities in certain simulation fidelity areas.

IV. Conclusion and Outlook

This paper aims to contribute to the evolving landscape of Search and Rescue (SAR) systems by providing a comprehensive overview of sensing and perception techniques applicable to SAR robotics. In doing so, we conducted a heuristic comparison of various sensor and hardware options, summarizing the findings in corresponding tables that highlight the main contributions of this survey. However, the authors feel obliged to emphasize that the selection of the SAR platform, along with the most suitable sensors and algorithms, as well as the choice of suitable simulation environments, depends on specific SAR mission requirements and specifications.

Although organizations like RoboCupRescue Robot League (RRL) [85] provide a platform for developing and benchmarking SAR robots in complex and hazardous environments, we discovered that there is a lack of a simulation benchmark to compare the hardware and software performance of various robots for SAR missions in harsh environments. We believe that constructing such a benchmark (e.g., a challenge) would be extremely useful as an initiative. Furthermore, the integration of several SAR robots in a simulated environment in this context would also aid in the analysis of real-world scenarios and may reshape the landscape of future SAR missions.

Looking ahead, the development of state-of-the-art perception and localization systems is vital for the further advancement of robotic SAR systems. This paper serves as a roadmap for navigating the intricacies of SAR software development, shedding light on the requirements and restrictions associated with SAR platforms. As the SAR field continues to evolve, this overview aims to guide future research and development efforts, fostering a more resilient and responsive SAR ecosystem for the benefit of those affected by disasters worldwide.

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