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A Survey on the autonomous exploration of confined subterranean spaces: Perspectives from real-word and industrial robotic deployments

Héctor Azpúrua [a,c,*], Maíra Saboia [b,1], Gustavo M. Freitas [d], Lillian Clark [e], Ali-akbar Agha-mohammadi [b,1], Gustavo Pessin [c], Mario F.M. Campos [a], Douglas G. Macharet [a]

[a] Department of Computer Science, Universidade Federal de Minas Gerais (UFMG), Brazil
[b] Jet Propulsion Laboratory, California Institute of Technology (JPL), USA
[c] Instituto Tecnológico Vale (ITV), Brazil
[d] Department of Electrical Engineering, Universidade Federal de Minas Gerais (UFMG), Brazil
[e] Department of Electrical and Computer Engineering, University of Southern California (USC), USA

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ABSTRACT

Confined and subterranean areas are common in many civilian and industrial sites, although they are hazardous for humans given the presence of noxious gases, extreme temperatures, narrow spaces, unhealthy oxygen levels, flooding, and collapsing structures. Therefore, exploration, routine inspections, and surveillance tasks can benefit from using autonomous mobile robots to improve safety by reducing the presence of humans in those scenarios. However, despite advances in the field, there are still challenges to overcome for confined and subterranean robot operation. Real word robotic exploration requires robust and reliable map generation, precise localization, safe navigation, and efficient path planning. These requirements make exploration in complex 3D environments with rugged terrain difficult. The challenge is increased when considering multi-robot teams, as there is no guarantee of a functional network infrastructure. Despite consistent increasing interest in the area, there is a lack of research summarizing the results and best practices for exploring such environments. Therefore, in this paper, we provide a review and discuss state-of-the-art robotic exploration techniques, including single and cooperative approaches with homogeneous and heterogeneous teams, with a focus on complex subterranean and confined 3D scenarios. We also present a comprehensive list of insights on open challenges and possible directions for future investigation in the topic.

1. Introduction

With the technological advances in current robotics hardware and software, new areas are open to using autonomous or semiautonomous mobile robots for various tasks, such as remote inspections and exploration. Confined areas are common in many industries where exploration, routine inspections, and surveillance tasks could benefit from using autonomous mobile robots. However, despite advances in the field, there are still challenges to overcome for robot operation in these situations.

Robotic exploration is defined as the act of "moving through an unknown environment while building a map that can be used for subsequent navigation" [1]. Despite autonomous exploration using mobile robots being a popular subject and a considerable amount of work already available on the most generic aspects of it, exploring real-world confined scenarios is still an open problem. Confined and subterranean areas are common in many civilian and industrial sites, although they are hazardous for humans given the presence of noxious gases, extreme temperatures, narrow spaces, unhealthy oxygen levels, flooding, and collapsing structures. Therefore, exploration, routine inspections, and surveillance tasks could benefit from using autonomous mobile robots to improve safety by reducing the presence of humans in these scenarios. However, despite advances in the field, there are still challenges to overcome for confined and subterranean robot operation.

From the robotics point of view, many of these scenarios also present challenging operational conditions for mobile robots,

* Corresponding author at: Department of Computer Science, Universidade Federal de Minas Gerais (UFMG), Brazil.

E-mail addresses: hector.azpurua@dcc.ufmg.br, hector.azpurua@pq.itv.org (H. Azpúrua).

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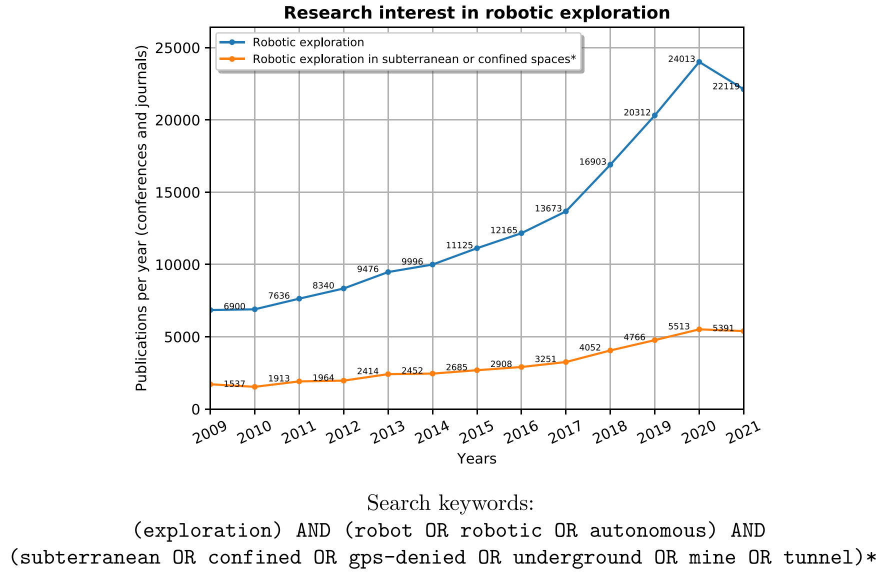


Fig. 1. The number of publications per year related to robotic exploration in traditional and confined spaces. Despite the increasing interest in general robotics exploration over the years, underground or confined exploration has a modest increase given the unsolved challenges faced by robots in those environments. Data extracted from [2].

such as rugged terrain, poor illumination, slippery ground, and the presence of water bodies. Real word robotic exploration requires robust and reliable map generation, precise localization, safe navigation, and efficient path planning. The challenge is increased with multi-robot teams in subterranean environments, as there is no guarantee of a functional network infrastructure. These requirements make exploration in complex 3D environments with rugged terrain difficult. Furthermore, additional communication infrastructure or cooperation mechanisms may be required to allow multi-robot exploration in such scenarios. These burdensome restrictions are gaining attention from robotic academia and industry; even the American *Defense Advanced Research Projects Agency* (DARPA) has created a four-year program dedicated to developing robot technologies to explore underground environments, the DARPA Subterranean Challenge (2018–2021) [3].

The physical, tangible form of a robot dictates the limits of its capabilities, and such limitations remain true when referring to terrestrial, aerial, underwater, or space robotic systems. A well-designed multi-robot system can overcome the limitations of only one robot or robot type, improving on some efficiency metric such as time or distance traveled [4,5]. However, raw efficiency improvements are not the only goal for multi-robot systems; robustness and fault tolerance are desirable characteristics, especially for industrial operations. Resilience is the capacity of a robotic system to recover its original function after partial damage and is "a characteristic that can be best achieved in the concept of robot teaming" [6]. Therefore, having only one robot performing exploration tasks may not be the most efficient method in terms of energy consumption, time, speed, or overall task robustness. The expected performance increase and the ability to have a resilient system are then some of the key motivators for using multiple robots working together.

Thus, this paper presents and discusses state-of-the-art robotic exploration techniques, including single and cooperative approaches with homogeneous and heterogeneous teams, focusing on complex subterranean confined 3D scenarios. Despite the consistent increasing interest in the area of general and subterranean exploration (Fig. 1), there is a lack of works summarizing the results and best practices for exploring subterranean environments. Different from other previous works such as [7], we do not focus on the mechanics of the robotic platforms per se; instead, we propose a taxonomy of exploration techniques, including descriptions of the exploration methods, the sensing requirements for mapping and localization in confined subterranean and GPS-denied scenarios, and summarize the results of the novel techniques employed in the 2021 DARPA Subterranean Challenge (2018–2021) [3].

The remainder of this paper is structured as follows. Section 2 presents the definition of a subterranean and confined environment and an analysis of the most appropriate sensors and methods to perform mapping and localization. Section 3 describes the state-of-the-art navigation for rugged terrains and for aerial platforms in confined spaces. Section 4 presents an overview of methods for 3D robotic exploration and Section 5 describes methods for multi-robot exploration. Finally in Section 6 we present state-of-the-art subterranean exploration and networking for exploration methods.

2. Confined and subterranean environments

Numerous modern buildings have a significant volume of underground industrial infrastructure such as sewers, pipes, caves, and other urban underground structures including subway tunnels [7]. Underground structures are more significant in industrial settings, such as the mining industry, dealing with both human-made and natural-made tunnels and caverns. Although the definition of a confined space can vary depending on legislation and country, it is generally recognized that many underground environments can be classified as confined spaces, i.e., areas where the entrances and exits are limited, not designed for continuous human occupancy, and where the ventilation systems are insufficient to oxygenate the interior or remove any contaminants from the air [8–10]. Subterranean and confined spaces can also be categorized as structured or unstructured. Most industrial and civilian buildings are structured, predictable environments with few uncontrolled variables, allowing a robot to know what to expect when navigating through them. However, in this work, we also consider unstructured environments such as natural caves, caverns, or disaster scenarios, which are more challenging to predict, requiring a robot to identify and adapt to environmental changes and variables. Fig. 2 shows a high-level classification of the characteristics of confined and subterranean environments.

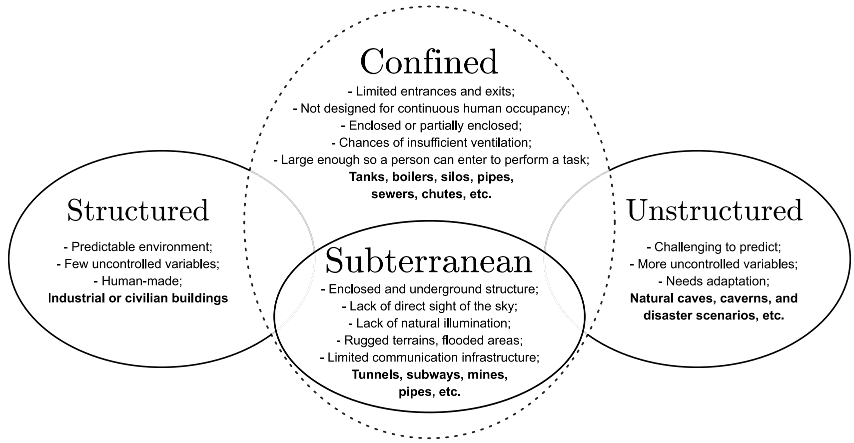


Fig. 2. High-level classification of the characteristics of confined and subterranean spaces.

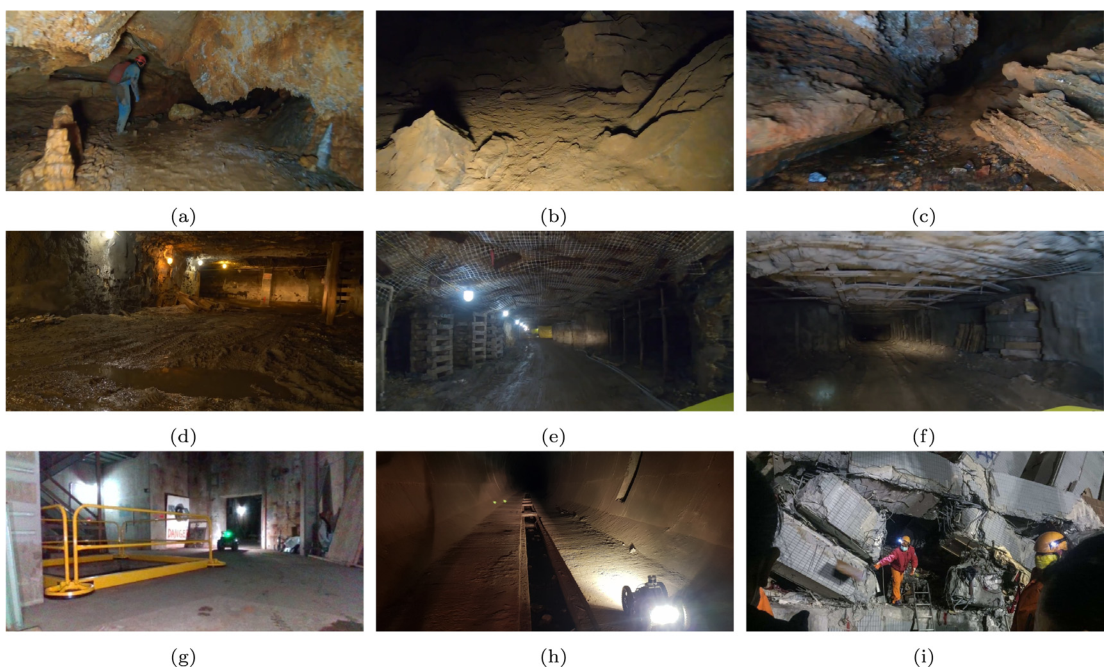


Fig. 3. Examples of confined subterranean spaces: caves (a–c), industrial tunnel systems (d–f), and an urban scenario (g) from the DARPA Subterranean Challenge [11,12], a subway-like structured tunnel system (h), and a collapsed building (i) [13].
Source: Adapted from [11–13].

Some risks related to confined spaces are the presence of venomous animals, noxious gases or excrement, extreme temperatures, narrow spaces, unhealthy oxygen levels, flooding, and collapsing structures, among others. Representative examples of confined underground spaces are shown in Fig. 3.

Operations in confined environments, such as maintenance and inspection, represent the bulk of regular tasks for workers in the mining industry, despite the inherent risks of such activities. Even though previous information and layout plans are available for some underground labyrinths, these can dynamically change over time, rendering plans and maps obsolete. In this sense, it is common to explore and remap the tunnels to assess safety for subsequent entrances. However, from the robotics point of view, many of those scenarios present challenging operational conditions. Irregular terrain, narrow and closed passages, harmful gases, lack of illumination, limited communication infrastructure (or reach), magnetic interference, lack of a GPS signal, slippery ground and floods are common characteristics of confined environments [14].

A particular challenge for ground robots in subterranean or enclosed scenarios lies in the terrain topography, which is commonly complex and unstructured, presenting a mix of flat and rugged areas (Fig. 4). These particular characteristics require any exploring agent to have efficient locomotion and navigation systems capable of overcoming obstacles while also considering energy consumption and payload capabilities.

2.1. Sensors for mapping and localization applications in confined spaces

The sensor suite for mapping and localization with an autonomous mobile robot inside confined and subterranean spaces requires careful evaluation given the possible harsh environment the equipment will face. Multiple works have studied and compared different sensor groups and technologies for subterranean spaces [15–19]; however, to the best of our knowledge, a comprehensive usability analysis of the most widely used sensors for these particular scenarios does not exist. Sensor analysis and

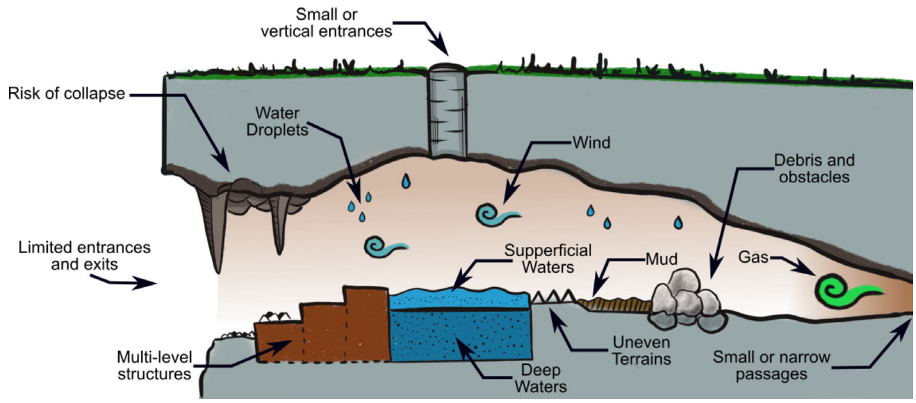


Fig. 4. Extension of the illustrative scenario presented in [7]. Known terrain challenges for robotic locomotion within a subterranean mine include limited entrances and exits, mud, presence of water bodies, uneven, rocky ground, rock piles and debris, strong wind gusts, gas, and dripping water from the ceiling, among others. *Source:* Extended from [7].

comparison in representative scenarios are fundamental, primarily since most manufacturers' sensor evaluation is performed in ideal situations and may not represent real-world robotic setups in harsh environments. In this sense, we do not intend to provide a comprehensive study of all possible sensor configurations or combinations, but rather a systematic analysis focused on a reasonable number of popular sensors appropriate for underground use.

Some of the most commonly used sensors for mapping in robotics are range sensors such as light detection and ranging (LiDAR), radar, sonar, passive cameras (stereo or mono), and active cameras (RGB-D or time-of-flight (ToF)). Other types of sensors can be used for direct/indirect localization and improve the overall mapping procedure, such as inertial measurement units (IMU), encoders, or other relative localization systems such as ultra-wideband (UWB) beacons or related wireless technologies.

Planar LiDAR sensors (Hokuyo 30ULX) or multiLine LiDAR sensors (Velodyne VPL-16) are some of the most prevalent devices for accurately mapping an environment in robotic applications, given their robustness and accuracy [15]. Most LiDAR technologies work using the ToF principle, where a single or multipoint laser is rastered horizontally using a group of spinning mirrors generating a point cloud. For single-beam LiDAR, attaching a motor or actuator to tilt the sensor continuously allows the acquisition of 3D range data. Since ToF LiDAR sensors estimate distance by measuring the time a laser takes to travel from the sensor and return, they can only provide data on the angle, distance, and reflectivity of a surface. There are other types of LiDAR technologies, phase shift or frequency modulated continuous wave (FMCW) LiDAR, or focal plane array (Flash) LiDAR, to name a few. These types of sensors have a high acquisition rate,[2] can work without external illumination and have a very long range that can reach beyond 150 m. The main drawbacks of this technology are size, weight, low spatial resolution at a distance (sparse points), the lack of texture and the use of rotating parts in most current sensor models. LiDAR system performance can also be degraded by extreme environmental conditions such as dust and severe fog [18,20,21], which can be common in many confined underground spaces.

Sound navigation and ranging (SoNAR) is an active technique for robot sensing using ultrasound waves. By estimating the ToF of ultrasonic pulses, it is possible to estimate object distances with high accuracy [22]. This method allows for good short-range precision at the expense of spatial accuracy and is found to work efficiently in several restricted humid environments where LiDAR does not work [23,24]. Another active approach for range measurements is radio detection and ranging (RADAR), which is an established technology for localization and obstacle avoidance in autonomous driving given its robustness to many environmental situations, and is also a feasible option for underground environments [25,26]. RADAR, like SoNAR, does not require light or temperature gradients to operate. Nevertheless, RADAR can be adversely affected by noise, spatial binning (resolution), and data corruption such as multipath reflections. Additionally, the antenna pattern may favor some dimensions over others [27]. Both SoNAR and RADAR have low energy consumption, off-the-shelf hardware, and, comparatively, they are less accurate than LiDAR in dry conditions. However, these range sensors outperform lasers in water since light refracts and reflects when underwater or surface water is present.

Monocular cameras can represent the world as a 2D matrix of pixels. These cameras can be monochrome or color (RGB), and a variable frame rate depends on the use case. Alone, these cameras cannot detect depth. However, with a calibrated camera and techniques such as structure from motion (SfM), it is possible to estimate a 3D representation of an environment [28,29]. Image information can also be used for landmark recognition. Planar images can help estimate motion and are generally used with other sensors such as LiDAR, encoders, or IMUs. A particular type of monocular camera called an event camera can provide information at a very high rate (microsecond resolution), with pixels responding asynchronously to changes in brightness [30]. Typical subterranean environments lack natural or proper illumination, generating problems such as the absence of visible textures, shadows, rapid brightness changes when using external illumination, and occlusions that could render most passive imaging sensors unreliable.

In contrast to traditional monocular cameras, depth cameras can produce 3D or depth data in addition to traditional images. Some examples of such systems are stereo cameras, RGB-D cameras, and ToF matrix cameras. Stereo cameras are a particular arrangement of multiple monocular cameras with known extrinsic and intrinsic parameters that allow the passive extraction of 3D information from a scene. Active RGB-D cameras can give depth and color simultaneously, even in low light conditions. In this sense, some of the most popular RGB-D cameras are the Microsoft Kinect and Intel RealSense product lines. Active RGB-D cameras project patterns of structured infrared light into a scene and use the sensed deformation of the patterns of objects in the scene to accurately estimate depth [31]. Despite being more robust to a lack of proper lighting, active cameras have degraded performance in brighter outdoor environments. Event cameras

[2] Commercial LiDAR sensors can reach scan acquisition rates of 10–50 Hz.

can also recreate depth, and recent research shows multiple techniques to generate 3D reconstructions using monocular and stereo event cameras [32,33]. In this sense, passive depth cameras suffer from the same limitations as passive monocular cameras, as they are sensitive to environmental illumination changes.

ToF matrix cameras are a particular case of ToF sensors that use a 2D array of ToF pixels, therefore providing a reconstruction of a 3D surface with very high accuracy, outdoor reliability, and speed. Structured light sensors are more appropriate for close ranges (less than 4 m) given that the depth accuracy significantly decreases with distance [34]. In contrast, ToF cameras have more general noise, but this measurement error does not increase as much with distance [17].

Close-range sensors such as bumpers, buttons, digital whiskers [35], or other tactile sensing systems are not widely deployed in real-world subterranean robotic mapping applications and are mostly used for collision detection given their limited actuation. This limited interaction means that more versatile range sensors generally substitute for them. Despite the limitations, some research has performed mapping with only with these types of sensors [36].

Odometry techniques are one of the most traditional localization methods, estimating the position of a mobile robot in time, using sequential sensor data relative to a specific coordinate system. The most popular sensors for odometry estimation in terrestrial robots are wheel encoders. These sensors can detect the rotational movement of a wheel and accurately determine how much it has turned. Encoder sensors can be mechanical, optical, magnetic, or work with electromagnetic induction. The rotational data alone can be used to estimate odometry via dead reckoning, but it is subject to cumulative errors and does not detect terrain problems such as slippery ground. Usually, other sensors are needed to estimate an absolute position [37]. In this sense, encoders and similar sensors are commonly used in conjunction with others such as LiDAR or IMUs to improve the overall robustness of simultaneous localization and mapping (SLAM) or visual-odometry estimators [38,39].

IMUs are electronic devices that can measure the orientation, velocity, and gravitational forces of the object to which they are attached using one or multiple accelerometers, gyroscopes, and magnetometers. These sensors are generally used in conjunction with others such as LiDAR, encoders, or cameras to improve the quality of a robot's localization estimate [40,41]. These sensors can provide internal algorithms for filtering, delivering high accuracy pose estimations in short time windows. Odometry estimation using only IMU sensors is prone to drifting; thus, other sensors are also needed to provide robust absolute localization estimation.

Other types of localization use radio signals for direct or indirect position estimation. UWB is a type of short-range low-battery radio communication, capable of accurate distance measurements using the ToF principle. Two methods are used for localization: time difference of arrival (TDoA) and two way ranging (TWR), which are capable of an indoor and outdoor localization resolution up to 30 cm or less depending on the environment and sensor quantity [42,43]. This localization mechanism generally depends on multiple fixed anchors arranged around the desired area, Moreover, newer research has developed methods that do not need fixed anchors or a previous estimate of the anchor's position [44,45]. This technique is robust to environmental situations such as low light, fog, rain, and typical signal problems of other wireless ranging solutions such as reflection. Other mechanisms for indirect wireless localization that were initially developed for traditional indoor and outdoor environments can also be adapted for subterranean setups such as WiFi [46,47], Bluetooth [48,49], TTE [50], and ZigBee [51].

In Table 1 we summarize the expected usability of many popular sensors used for map generation and exploration in confined and subterranean scenarios. The analysis and results are meant to guide sensor selection, given the perils and conditions of an underground space. Not all conditions can be considered; consequently, we selected the critical conditions from several research studies. Since there is an intractable number of combinations among sensors, the individual sensor performance is used for scoring.

2.2. Map representations

The map representation used for a particular environment must be compatible with the sensor used and the mapping task's final goal: mapping accuracy or a less detailed map for navigation. In this sense, the most common map representations can be grouped into topological maps and metric/geometric maps. These approaches can also be divided into 2D and 3D map representations, where 2D maps are more suited for structured indoor spaces and 3D representations more suited for unstructured outdoor environments. In general, maps are used for navigation and environment reconstruction/analysis within confined spaces. The quality of a map will also reflect on the type of path planning performed: highly detailed maps allow for fine-grained navigation capable of avoiding obstacles, overhangs and reducing possible environmental hazards at the cost of extra memory and CPU consumption. In this sense, there exists a trade-off between map accuracy and the computational capability of a robot. Some map characteristics are best captured with fully 3D representations; however, there are cases where less complex maps will suffice, mainly when used as dynamic local obstacle maps.

A topological map is an abstract description of the structural characteristics of an environment. For example, topological maps can represent the connectivity of different places such as rooms, floors, or buildings connected by a sequence of robot actions. Generally, these types of maps are modeled as graphs, where nodes are locations, and arcs/edges are ways to reach them [52,53]. On the other hand, metric maps capture an environment's geometric properties, similar to a floorplan. The distinction between metric and topological maps can be considered fuzzy since most working topological approaches also rely on geometric information. In practice, metric maps are finer-grained than topological maps, but this comes with an extra computational cost [54].

Occupancy grids were one of the first probabilistic map representations used by mobile robots [55]. These maps discretize an environment into small portions called grid cells, and every cell has information about the area it covers, such as the probability of cell occupation.

Occupancy grids have great representation capability because no prior information of the map or model of the environment is needed. Traditional occupancy grids are capable of multiple map resolutions but focus on only two dimensions. Other less popular 2D map representations are feature-maps [56] and point maps [57].

Thrun et al. [58] developed a hybrid metrical and topological approach. In this case, metric grid maps are learned using artificial neural networks and naive Bayesian integration and topological maps are generated by partitioning the grid map into regions. The author claims that by combining both paradigms the accuracy advantages of grid maps are improved by the efficiency of the simpler topological maps.

If an environment can be modeled as a height function $h = f(x, y)$ where x and y define a point in the environment and h is the height, then elevation maps or 2.5D maps are a reasonable choice. In an elevation map, the height value is stored in a discrete location, meaning that open and single-level scenarios can be

Table 1
Hardware for mapping and localization in confined and subterranean environments.

Hardware	Example device	Usability criteria in underground spaces																			Score[c]
		Non line-of-sight	High bandwidth	High precision	High resolution	Fast acquisition time	Remote sensing	Long/middle range sensing	Can capture 3D data	Rob. to poor illumination	Rob. to fog/etc.	Rob. to lack of texture	Rob. to drifting/mud	Rob. to water bodies	Lower CPU/GPU reqs.	Embebbed processing/filters	Rugged/Water resistant	Few/No moving parts	Lightweight/Small	Used in DARPA's SubT	
Direct Localization[a,b]																					
GPS	U-blox NEO-6M	○	–	○	○	○	○	○	–	○	○	○	○	○	●	●	●	●	●	○	0.29
UWB	DWM1001	◐	○	◐	◐	●	●	●	–	●	●	●	●	○	●	●	●	●	●	●	0.81
Wheel encoder	USDigital S1	–	–	◐	●	●	–	–	–	●	●	–	○	●	●	●	●	○	●	●	0.81
IMU/Accel./Gyro	Xsens MTi-610	–	–	●	●	●	–	–	●	●	●	●	○	●	●	●	●	●	●	●	0.93
Wireless Localization[a,b]																					
Bluetooth	nRF52840	○	◐	○	◐	◐	●	◐	–	●	●	●	●	○	◐	○	●	●	●	●	0.58
ZigBee	Xbee S2C	○	◐	○	◐	◐	●	◐	–	●	●	●	●	○	◐	○	●	●	●	●	0.58
NFC/RFID	NXP PN532	○	◐	●	○	◐	◐	◐	–	●	●	●	●	○	◐	○	●	●	●	○	0.58
WiFi	Real. RTl8723DE	○	●	○	◐	◐	●	◐	–	●	●	●	●	○	◐	○	●	●	●	●	0.67
TTE (Through-The-Earth)	CanaryCommpac	●	◐	◐	◐	◐	●	●	–	●	●	●	●	○	◐	◐	●	●	○	○	0.67
Mapping/SLAM[b]																					
Event Camera	DAVIS346	–	–	●	◐	●	●	◐	○	◐	○	○	●	○	○	◐	●	●	●	○	0.53
Monocular RGB Camera	FLIR Firefly S	–	–	●	●	●	●	◐	○	○	○	○	●	○	○	○	●	●	●	●	0.56
IR ranging	GP2Y0A710K0F	–	–	◐	○	●	●	◐	○	●	○	●	●	○	●	●	◐	●	●	○	0.62
Passive 3D Camera (Stereo)	Stereolabs ZED	–	–	◐	●	●	●	●	●	○	○	○	●	○	○	◐	●	●	●	●	0.65
Touch	Bumpers/whiskers	–	–	●	○	●	○	○	○	●	●	●	●	●	–	–	●	○	●	●	0.67
Thermal/Spectral Camera	FLIR A700	–	–	◐	◐	◐	●	●	○	●	◐	●	●	◐	○	○	●	●	●	●	0.68
Sonar	MaxBotix MB1000	–	–	◐	◐	◐	●	○	○	●	●	●	●	●	●	●	◐	●	●	○	0.71
Radar	XM1321	–	–	◐	◐	◐	●	●	○	●	●	●	●	●	◐	◐	●	●	◐	●	0.71
Rotating sensor (LiDAR)	LiDAR + motor	–	–	●	●	●	●	●	●	●	◐	●	●	○	○	●	◐	○	○	●	0.71
Single-line LiDAR	Hokuyo 30LX	–	–	●	●	●	●	●	○	●	◐	●	●	○	◐	◐	●	◐	◐	○	0.74
Active 3D Camera (ToF, IR)	Intel D435i	–	–	●	◐	●	●	◐	●	●	○	◐	●	○	○	●	●	●	●	●	0.74
Multi-line LiDAR	Ouster OS1	–	–	●	●	●	●	●	●	●	◐	●	●	○	○	◐	◐	◐	◐	●	0.74

● = criterion fully covered; ◐ = partially covered criterion; ○ = non-covered criterion; "–" = not applicable.
[a]Only evaluated for its localization accuracy.
[b]Evaluated as standalone devices.
[c]Normalized score given by weighted sum of valid criteria for the item (Higher score is better).

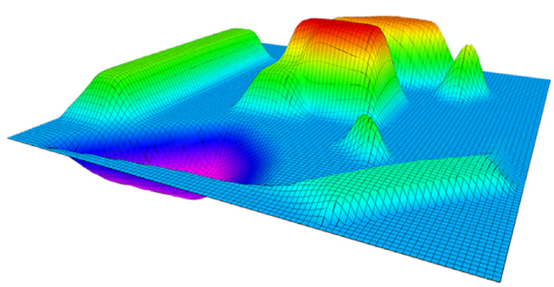


Fig. 5. Grid map example of an elevation map in a unstructured outdoor scenario with multiple obstacles.
Source: Adapted from [60].

represented efficiently given that no other vertical surface or overhangs exist. Elevation maps are common in planetary exploration given the certainty of no vertical structures other than the ground floor [59]. [60] developed an efficient method to generate elevation maps or 2.5D maps, called GridMap (Fig. 5). The method is fast enough for use in real-time surface reconstruction and terrain interpretation for uneven terrain. It supports a multiple layer system for different mapping metrics, such as altitude, angle, and roughness. It is currently used for multi-legged robot navigation, such as the ANYmal platform [61]. In [62], the authors present a hybrid 2.5D map representation called 2.5D-NDT, which simplifies a 3D occupancy grid into an elevation map of traversable areas.

Although 2D and 2.5D representations can work correctly in open areas, a full 3D model of the environment is needed when the robots can also move under or above the terrain. A point cloud can represent occupied points over a 3D environment with great detail, but it is a suboptimal representation that is not generally used directly for real-time planning. A significant number of robotics applications require a fast and memory-efficient probabilistic map representation, with the capacity of representing free and occupied areas. In this sense, one of the most popular techniques for probabilistic 3D mapping is OctoMap, which uses efficient modeling based on Octrees to minimize space and memory [63]. Octrees are an efficient tree-type data structure in which each internal node has exactly eight children, commonly used for partitioning a three-dimensional space by recursively subdividing it into octants [64]. In this regard, OctoMap can model arbitrary environments without prior assumptions about them, allowing empty, free, and unexplored spaces with arbitrary size and resolution to be recorded, as shown in Fig. 6. OpenVDB, is another hierarchical tree data structure with efficient access methods to discretized volumetric data that has also been reported for robotic mapping applications [65].

Other types of 3D representations can deal with obstacles directly, such as Voxblox, which uses Euclidean Signed Distance Fields (ESDFs) [66]. The method proposed by [66] employs Truncated Signed Distance Field (TSDFs), initially designed for surface mesh reconstruction and common in computer graphics and vision, to incrementally generate ESDFs. The authors showed that in some cases, the proposed method can outperform OctoMap in speed. An example of a Voxblox-generated map can be seen in Fig. 7. TSDFs are also used as a method for representing occupancy [67].

Hybrid approaches can also benefit from the use of three-dimensional topological data. In [68], a feature-based map generated from a visual SLAM system is converted into a 3D topological

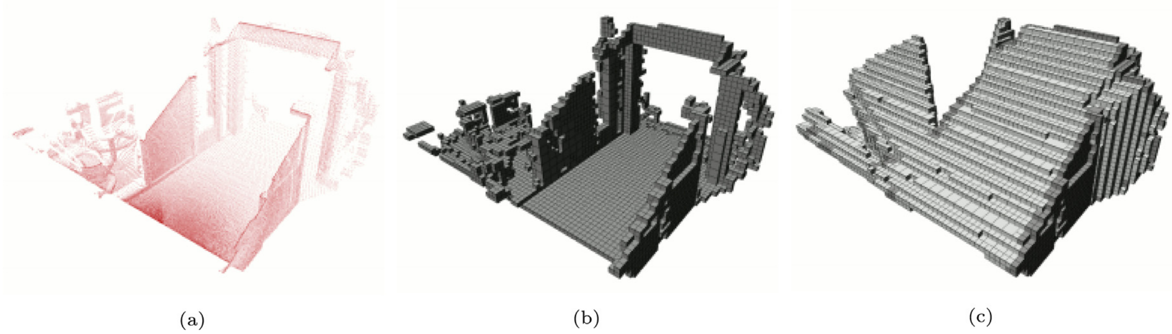


Fig. 6. Given multiple point-clouds a full detailed map can be reconstructed using OctoMap: (a) a point cloud of the environment, (b) the occupied cells and (c) free cells [63].
Source: Adapted from [63].

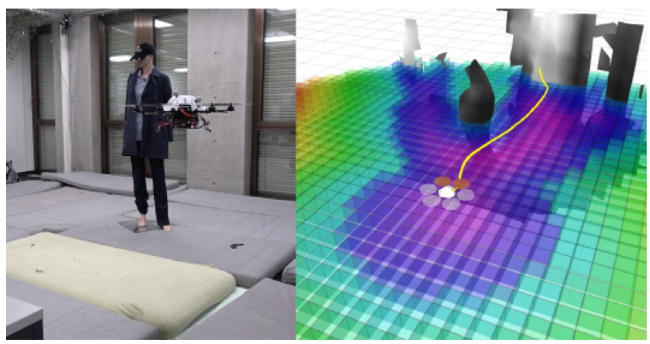


Fig. 7. A Voxblox-generated map generated by a small UAV. The TSDF is shown as grayscale mesh, and the ESDF is shown as a single horizontal slice of the 3D grid.
Source: Adapted from [66].

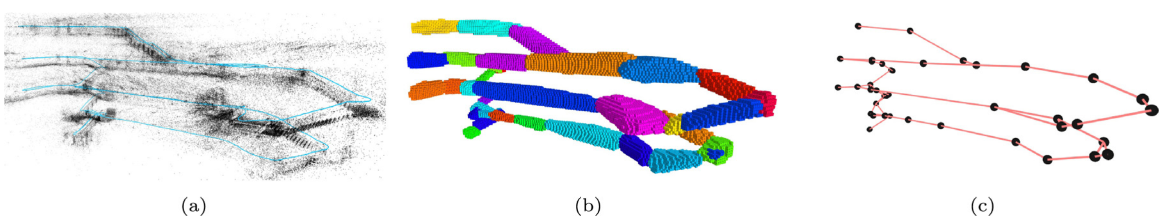


Fig. 8. A topological map generated by point clouds: (a) sparse point cloud, (b) topological cluster of convex free space, and (c) the derived simplified navigation map between the clusters.
Source: Adapted from [68].

map using the Topomap algorithm. A topological map is created by extracting the occupancy information from the point cloud, and then a set of convex free-space clusters are estimated and used as the topological map's vertices (Fig. 8).

Another type of map representation with high description capabilities is a mesh. A mesh can be defined as a collection of vertices, edges, and faces that define a polyhedral object's shape. Generally, the faces of a mesh are triangles but may also be other geometrical figures. Compared to 2.5D solutions, 3D mesh surfaces allow for planning and navigation in arbitrary complex environments, including multi-level environments. Meshes can be used for navigation in terrestrial robotics and are useful for applications in uneven terrain [69] (Fig. 9).

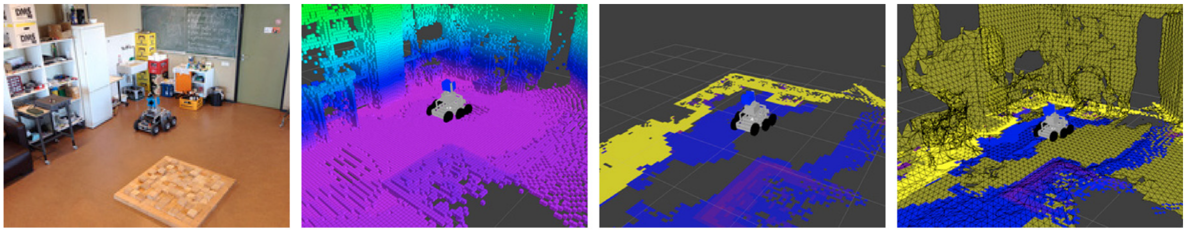
Table 2 presents the characteristics of the most commonly used map representations and the expected usability in confined spaces.

3. Path planning in confined spaces

Most nonreactive exploration techniques that work in real scenarios rely on safe and efficient ways to navigate the environment. Although navigation embodies different methods such as control, localization, mapping, and path planning, in this section, we focus on path-planning methods in confined, GPS-denied scenarios since these environments have particular locomotion challenges for autonomous aerial or terrestrial platforms that need to be addressed before the exploratory behavior begins.

3.1. Path planning for terrestrial robots in rugged terrains

A robot performing exploration tasks in rugged confined spaces will need to traverse complex 3D environments; therefore, traditional planning techniques that rely only upon 2D information are not adequate [73]. For exploration robots that rely on terrestrial locomotion, path-planning methods that address terrain topography and the characteristics of the environment to create safe and traversable paths are critical for the mission's success. In this sense, 3D navigation has been studied primarily for outdoor scenarios, including space exploration [74,75]. Several works have studied the majority of path-planning algorithms [76–78]; nevertheless, few works deal with the problem of path planning in rugged terrain. Given the complexities and memory requirements for larger 3D maps, current navigation



(a) (b) (c) (d)

Fig. 9. Map representations to estimate trafficability in 3D in uneven terrains: (a) real scenario, (b) Octree representation, (c) 2D map, and (d) mesh representation. *Source:* Adapted from [69].

Table 2
Map representations characteristics and expected usability in confined spaces.

Map representation[a]	Dim.			Criteria					Remarks[b]
	Two dimensional (2D)	Elevation based (2.5D)	Three dimensional (3D)	Low memory consumption	Low CPU overhead	Allows multi-level envs.	Multiple resolutions	Open source	
Feature/Line maps [70]	●	–	–	○	○	○	○	○	An intractable number of lines is necessary for a correct representation of complex terrain and obstacles.
Occupancy grids [55]	●	–	–	◐	●	○	◐	●	Traditional occupancy grids are limited to 2D. Useful for obstacle avoidance, local traversability maps, or subterranean structured planar environments without multiple levels or challenging topography.
Topological maps [53]	●	–	●	●	●	●	○	●	Can be used in conjunction of other types of maps, including 3D maps to improve path planning and semantic analysis.
Elevation maps [61]	●	●	–	●	◐	○	◐	●	Cannot deal correctly with overhangs or multi level environments, *i.e.* areas with ceiling. Useful for local planning.
Point clouds [71]	●	●	●	○	○	●	○	●	Great descriptive capabilities, not optimized for memory usage or fast search.
Meshes [72]	–	●	●	◐	◐	●	●	●	Capable of representing almost any shape. Memory-optimized. Can use textures. Surface extraction could be challenging with noisy datasets.
Voxblox [66]	●	–	●	●	●	●	○	●	Novel description using Signed Distance Fields. Memory and space optimized.
Octrees [63]	●	–	●	●	●	●	●	●	Great descriptive capabilities of almost any three dimensional shape. Allows multiple resolutions and its memory and space optimized.
OpenVDB [65]	●	–	●	●	●	●	●	◐	Hierarchical tree data structure with efficient access methods. Benchmarks shown that is faster than Octrees in some cases.

● = criterion fully covered; ○ = non-covered criterion; "–" = not applicable.
[a]Evaluated as standalone map representation.
[b]Map combinations could overcome weak aspects of an individual representation, *i.e.*, point clouds with topological maps.

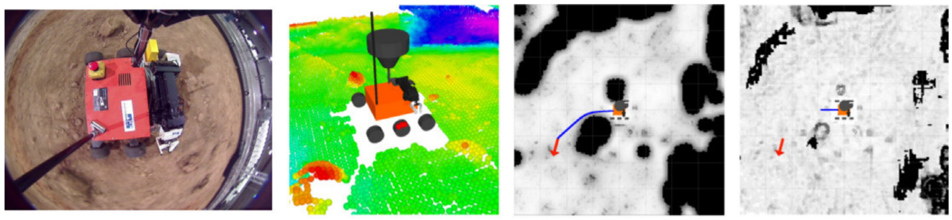
algorithms generally use a segmented approach for path planning via local and global maps: global navigation mechanisms aim to guide the vehicle to its destination, while local navigation addresses obstacle avoidance and other rapid environmental changes.

As seen in many works in the area, graph representations allow increased flexibility in representing terrain topography and multi-level scenarios. Graphs are conceptual structures composed of nodes or vertices connected by arcs, where weights can be assigned to the arcs. Thus, a graph search algorithm can find the path with the lowest cost between two nodes. There are several graph-based search algorithms commonly used for robotic navigation [79]. Approaches such as A* [80] or D* [81] use heuristics to guide the search to an optimum solution in less time, given that the heuristic is admissible. A heuristic is admissible if it does not overestimate the cost of reaching the goal, i.e., the estimated cost is not higher than the lowest possible cost from the current point in the path.

Other popular search algorithms, such as rapidly exploring random trees (RRT) [82] and optimum rapidly exploring random trees (RRT*) [83], adopt a probabilistic strategy that generates a tree from a set of sampled vertexes. If computing efficiency is not a limitation, probabilistic or heuristic path generation algorithms may not be the most appropriate for path generation in complex 3D scenarios since slight deviations of the best path could cause robot failure. In those cases, deterministic optimal path search algorithms may be used, such as the Dijkstra Algorithm [84].

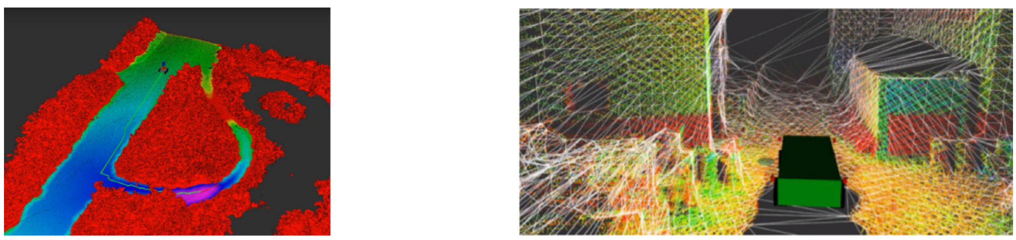
In [85], the authors propose a path-planning algorithm for a planetary rover that considers a robot's dynamic mobility over 2.5D elevation maps. The authors use Dijkstra's algorithm for path planning, considering a cost function composed of terrain roughness, terrain inclination, and path length. These metrics are normalized, and the trade-off between them is balanced through weights. Thus, the algorithm evaluates the relevance of each one while finding navigable paths. In [86] the authors presented a robot-centered 2D drivability map generated from eight RGB-D sensors measuring the 3D geometry of the terrain around the robot using 2.5D egocentric height maps (Fig. 10). Other works use a 2D projection of the drivable surface, assuming that there are no overhanging structures the robot will drive under or over [87]. The drivable surface is modeled as a graph considering traversability and drivability costs as edge and node costs. The optimal path is estimated via a graph search A* algorithm using the Euclidean distance as the heuristic.

Raja et al. [88] presented a motion planning algorithm for a six-wheel rover on rough terrain. The algorithm uses potential



(a) (b) (c) (d)

Fig. 10. Navigation pipeline for rovers using multiple RGB-D sensors: (a) wide-angle overhead rover camera, (b) point cloud color-coded by height, (c) drivability map, and (d) obstacle map.
Source: Adapted from [86].



(a) (b)

Fig. 11. Mesh-based navigation examples. (a) Path planning instance showing wire-frame rendering of a mesh and the visualization of vertex costs from red (higher cost) to green (lower cost) presented in [94]. (b) The robot-centric watertight mesh generated for local navigation proposed by [95]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Adapted from [94,95].

fields associated with the terrain, where the proposed function consists of attractive, repulsive, tangential, and gradient forces. The gradient force is a function of the rover's roll, pitch, and yaw angles derived from the robot kinematic model. The tangential force is used to avoid local minima and concave-like obstacles. The algorithm tries to find safe paths avoiding routes with high gradient values. The authors assign weights to the potential field function components, which are optimized using genetic algorithms. The proposed method also evaluates the vehicle's wheel velocity to ensure stability and prevent wheel slippage.

In Takker et al. [89] it is presented a framework for resilient autonomous navigation for challenging environments. This work exploits the redundancy and heterogeneity of multiple sensing modalities and achieves several levels of resiliency, including recovery actions upon system failures. The proposal generates online traversability estimates of a point-cloud by using a multi-step procedure and defining ground and obstacles points using a line-fitting approach [90]. In [91], the authors proposed a learn-based method for traversability analysis. Instead of using computational expensive geometrical analysis, the authors propose a neural network architecture to learn the traversability costs distribution in point-clouds of subterranean environments. The solution was validated in different sets of unstructured and complex terrains.

In [92], the authors propose a multi-objective path-planning approach for mobile robots for planetary exploration based on the A* path search. Given that extraplanetary surfaces can contain irregularities and hazardous situations such as holes, hills, and rocks, the method attempts to minimize the difficulty, danger, elevation, and length of the path. The authors also used weights to set the trade-off between the objectives.

Modern approaches explore mesh structures for navigation, as shown in Fig. 11. By converting a mesh into a graph, the authors use the Dijkstra path search exploiting the mesh triangles' topological connections and their costs [93,94]. Another planning step uses a wavefront propagation over the mesh surface to generate a potential field from each accessible position to the goal. Other approaches create a watertight mesh for local navigation [95].

A complex point not explored heavily in recent navigation research is the interaction of a cable tether with the terrain as presented in [96]. In this work, the authors focused on generating safe paths for rappelling rovers in complex terrains, considering the terrain–tether interactions, and the stability and reachability constraints of the rappelling system. The ABIT* algorithm [97] is used for path generation. In [98], is presented a tether-aware frontier-based exploration algorithm for planar 2D spaces with guaranteed tangle-free global paths. A robot with a retractile and limited tether estimates the expected length of the cable tether from the current robot position to a frontier and uses homotopy to compare it to the shortest possible length to reach this frontier from the base station. If these lengths are distant, the method calculates a new path with a similar homotopy signature of the smaller path to return the robot to the shortest tether configuration.

3.2. Aerial path planning in confined spaces

Three-dimensional path planning for UAVs allows avoiding obstacles and overcoming structural constraints of an environment at the cost of an increased complexity dealing with the dynamic and kinematic constraints of aerial platforms, especially in GPS-denied scenarios with narrow corridors. As with 3D terrestrial path planning, many methods model the aerial path-planning problem as a graph problem and use algorithms such as visibility graphs [99], an RRT [82], and other approaches explore heuristics such as bio-inspired algorithms. In this sense, having efficient paths is even more critical with aerial platforms than with their terrestrial counterparts, given their limited autonomy, which is greatly affected by the carried sensing payload [100]. Planning for aerial platforms can be observed as a complex multi-objective optimization problem, with several platforms and environmental constraints.

Given the high computational complexity of planning in a cluttered and complex 3D environment and the frequent re-planning needed to increase mission robustness, some works reduce the dimensions of the planning space to improve efficiency

[101–103]. However, these techniques have limitations when dealing with more complex environments.

According to the environmental information available, the traditional classification of path-planning algorithms for UAVs can be online/local or offline/global. When considering exploratory behavior, most algorithms can be classified as online, allowing rapid course changes to avoid obstacles and re-route the robot to the most informative areas [104]. Unexplored and unknown regions of the map can be dangerous for aerial platforms considering that there may be overhangs or other nontrivial obstacles; therefore, aerial path planning in confined environments is generally performed exclusively in the known free space.

Several works define the taxonomy for UAV path-planning algorithms as sampling-based, node-based, mathematical model-based, bio-inspired, and multi-fusion-based [105]. Most algorithm types can deal with dynamic environments; however, bio-inspired algorithms such as genetic algorithms [106] and ant colony optimization [107], are generally slower to compute and thus more appropriate for static environments [108]. On the other hand, recent research using deep neural networks coupled with traditional path planning has achieved highly agile and fast movement in dynamic environments [109]. In [110], the authors present a navigation planner algorithm using neural networks for collision avoidance. A neural network predicts a collision's cost given a sequence of possible motion primitives in the robot action space, considering the robot's linear and angular velocities and a depth image from an RGB-D sensor. The algorithm was tested in unseen subterranean environments with a micro aerial platform capable of following a global plan while avoiding small obstacles in a visually challenging environment.

Sampling-based algorithms generate a set of nodes from samples of the environment and then connect these nodes using some metric or heuristic, such as the nearest neighbor. Sampling algorithms are simple to implement and fast to compute. Some popular sampling algorithms are the RRT family of algorithms [78,111,112], probabilistic road maps (PRMs) [113], 3D Voronoi [114], and visibility graphs [99], among others.

Node-based algorithms can generally generate an optimal path given the set of nodes from a graph and their relations, which can be a distance metric or other type of weight. Node-based methods differ from ground-based path planning in how the graph is generated and how the weights are initialized. Node-based algorithms such as Dijkstra's algorithm are optimal but can take longer to compute than their sampling-based counterparts. Recent algorithms such as Lazy Theta* [115] and critical obstacles and surrounding point set (COSPS) perform efficient path planning using graphs for online exploration, considering a safe distance from all obstacles.

Mathematic model-based algorithms describe the complete workspace in a typical optimal optimization form, including the kinematic and dynamic constraints, bounding the cost function with those inequalities, and thus are commonly slower to compute and more appropriate for offline execution. Some mathematic model-based algorithms are mixed-integer linear programming, binary linear programming [116], non-linear programming [117], and artificial potential fields. Artificial potential fields are prone to local minima, and it is necessary to use additional strategies to avoid them. Finally, fusion-based methods can merge or combine several algorithms to overcome sub-optimal or slow path computation [118,119].

Many of the algorithms mentioned above produce paths that need smoothing to prevent abrupt navigation changes in actual flights [120]. Some works have used Bezier curves, B-splines, cubic-polynomial splines, or moving averages to smooth 3D paths for UAVs.

4. Robotic exploration

As the act of robotic exploration means moving through an unknown environment while building a map, good exploration strategies should generate complete maps (or close to it, given the environment limitations) in the minimum time possible. Exploration is essential when dealing with coverage and mapping of an unknown region. The basic principles of exploration were described by [121], which can be condensed as estimating the "next-best-views" in an unknown scenario [121].

The robotic exploration taxonomy can be divided into two large groups: two-dimensional and three-dimensional exploration. Those groups can also be subdivided into single or cooperative robots or classified by exploration strategy. The principal techniques used for exploration are frontier-based, sampling-based, information-based, and hybrid or random approaches. In the context of exploration, a frontier is defined as a region located at the boundary between the already explored space and the unexplored [1]. Fig. 12 depicts a high-level taxonomy of typical robotic exploration approaches. Given the significant number of options and variants of the various exploration techniques, selecting the best algorithm depends upon the application at hand, the environment, and the available resources [122].

Two-dimensional exploration focuses primarily on structured indoor environments, such as buildings, offices, or cities. Buildings and other related structures are designed by humans (for humans) with standard and recognizable geometric features that some exploration algorithms can exploit. These approaches generally do not consider multiple levels or slopes and therefore are limited by more straightforward representations of the environment. This work focuses primarily on three-dimensional exploration since the terrain topography, obstacles, and multiple levels generally found on confined and subterranean environments require a more detailed understanding of the environment, unattainable with classic two-dimensional exploration approaches. Recent works have presented an in-depth analysis of multiple 2D exploration methods for readers unfamiliar with traditional exploration strategies [123,124].

4.1. Three-dimensional exploration

Three-dimensional exploration increases the complexity over traditional 2D exploration algorithms with the benefit of an increased range of real-world outdoor applications, ranging from drone inspection and reconstruction [125] to cave mapping [126]. Performing exploration of an unknown 3D environment requires the acquisition of viewpoints over areas with unknown structures and textures in a problem commonly called the "next-best-view" selection [121,127].

A naive extension of 2D exploration methods into three dimensions introduces several challenges to overcome. For example, the popular frontier-based exploration method, first introduced by Yamauchi [1] had as central idea the visitation of boundaries between unknown areas and the known open space. When used with raw, sparse, and noisy 3D sensors such as depth-cameras or 3D LiDAR, a naive frontier-based approach fails to accurately capture the differences between unoccupied and unknown space as those areas are often closely colocated [128]. Additionally, the sparse sensor information is easily mismatched for unknown free space, such as floor areas between LiDAR lines, yielding exploration strategies that drive a robot to produce a comprehensive local map at the cost of reducing the expansion rate of the global map (see Fig. 13).

A particular challenge for 3D exploration is computational complexity. Maintaining a dense map in two dimensions is computationally tractable; however, a 3D dense map can quickly

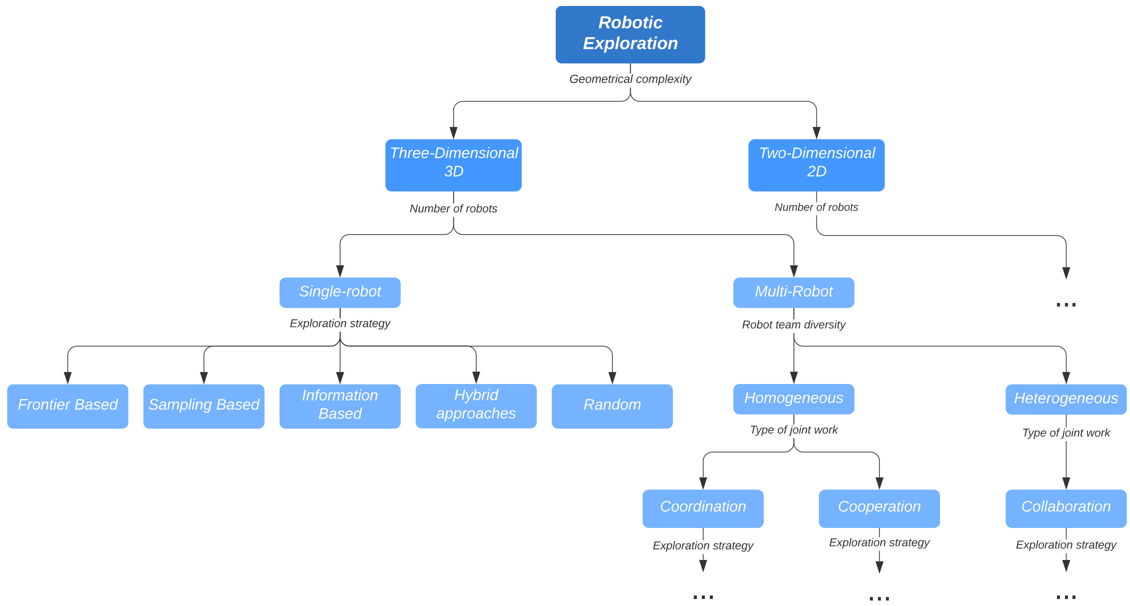


Fig. 12. High-level robotic exploration taxonomy.

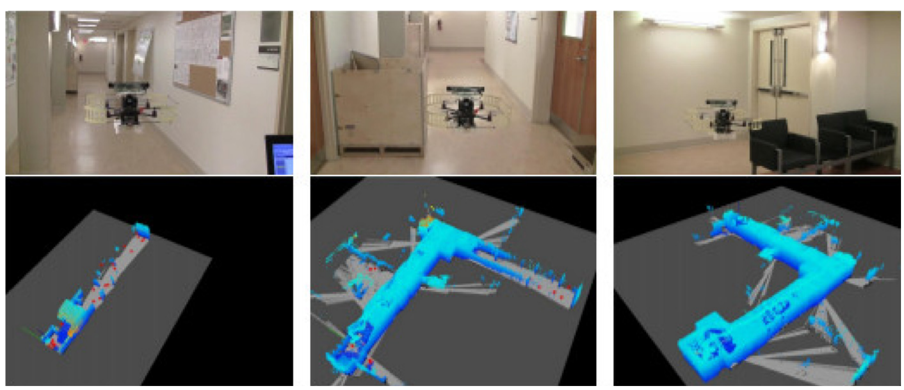


Fig. 13. An example of the sequential 3D exploration of a single-floor hallway using a quadrotor and a depth camera. *Source:* Adapted from [128].

become intractable if efficient mapping and exploration methods are not used. This limitation is critical for small mobile devices with limited payload and autonomy. In this sense, [128] uses an efficient representation of the environment such as Octrees and performs exploration for single and multi-floor indoor scenarios with quadrotors. The proposed method shows a stochastic differential-equation-based exploration algorithm that only uses the known occupied space in the current map instead of the known free space and unknown space. In this method, the evolution of the stochastic differential equation simulates the expansion of a particle system with Newtonian dynamics, and the frontiers are detected as regions with more particle expansion. Other works have validated that efficient 3D next-best-view estimation can be achieved using Octrees and ray-tracing. In this idea, [129] proposes fast hierarchical sparse ray-tracing over partial Octrees. Multiple methods for next-best-view and information gain estimation, such as hierarchical and sparse ray-casting, are also benchmarked in [130].

Many aerial exploration methods also rely on the free and known space extracted from an Octree to plan and perform decision making. Zhu et al. [131] presented a 3D frontier-based exploration method named 3D-FBET using the state-changed space in a 3D map generated by Octrees. The method uses the transformation between two robots to find the correct transformation between multiple robots' map frames. By exploiting the probabilistic nature of Octrees, the resulting registered map is correctly aligned. In [132], the authors present an exploration algorithm for 3D spaces with quadrotors that uses a potential information field to guide a robot toward a goal while being repelled by obstacles (Fig. 14). They use a multi-objective function to select the best next frontier to visit considering distance and information gain. Then an artificial potential field (APF) guides the robot to the goal. The proposed method only employs the goal region and local information around the robot, which reduces the computational complexity and can work online. The repulsive forces of repeatedly viewed voxels are increased to reduce local minima. Other works improve on the classical 3D-FBET by using not only local but a global frontier set with different resolutions, reducing the noise of the frontier locations by using clusters and by selecting the best next frontier using a information-based approach [133].

In [134], the authors propose a method for quadrotors that allows fast exploration by maintaining the fastest speed possible while minimizing the angular movement and rotation of the robot at the first steps of the exploration procedure. The method generates instantaneous velocity commands based on the currently observed frontiers using an RGBD camera (dense range sensor) through an RRT* path-planning algorithm. If there are no more locally observable frontiers, the method falls back

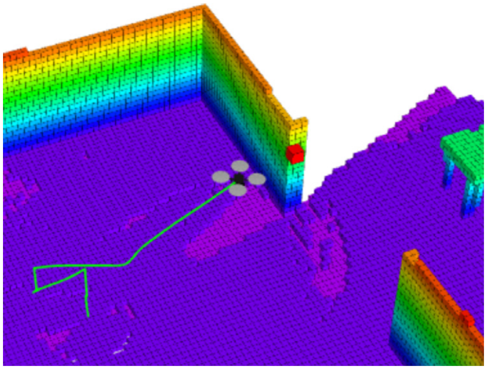


Fig. 14. A UAV exploring an indoor 3D space using an Octree representation. The robot carries a dense depth sensor and a linear LiDAR.
Source: Adapted from [132].

to traditional frontier exploration methods. Exploration methods that perform online planning for quadrotors in a receding horizon fashion, selecting the "Next-Best-View" (NBV) by sampling possible future configurations in a geometric random tree are proposed in [125,135] (Fig. 15). Newer approaches of aerial exploration in this vein use a combination of the NBV sampling and frontier-based approaches to minimize the cost of detecting the location of unexplored areas at extensive environments [136].

In [137], the authors present an uncertainty-aware path-planning strategy for autonomous aerial robots classified as active perception. The proposed method is a multistep procedure where the exploration gain is estimated, and an RRT* planner creates a geometric tree in the mapped free space. This mapping uses the camera sensor's field-of-view to estimate how much volume is mapped at the path points. The reduced uncertainty of reobserved voxels is also considered in the planning step. In a second step, possible deviations from the original path are planned, aiming at possible configurations that could yield improved localization or mapping confidence.

Dai et al. [138] presented an algorithm for information-theoretic 3D exploration using UAVs. The method uses sparse ray-casting to estimate the information gain over the next-view candidates. A frontier utility is measured as the ratio between information gain (entropy) and the travel path time to reach a frontier. The feasible paths are generated by an informed RRT* algorithm exploiting an Octree's free known voxels. A sphere around the robot performs a collision check. Other works also use some kind of ray-tracing procedure over the view frustum of the robot to estimate the volumetric information gain of the frontiers [139–141].

Other types of robotic exploration, such as degrees of freedom (DoF) physical exploration, can also be performed using Information Theoretic approaches. Degrees of freedom exploration can be defined as the challenge of autonomously discovering and learning how to manipulate the environment by identifying promising points of interaction and pushing or pulling object parts to reveal new DoF and their properties. Opening drawers or doors, pushing a box, or pressing a button to switch on the light, can all be considered DoFs of the environment. In that direction, [142] presents a method to decide where to explore based on the entropy reduction about the current robot's belief about the DoF. They propose a probabilistic belief representation to capture the robot's current knowledge state and a method to estimate the expected information gain from a set of new actions. Their method was validated in a real scenario with a PR2 robot, with motion planning and execution.

Many of the works on three-dimensional exploration are projected with aerial platforms in mind, given that terrestrial platforms are limited by the terrain topography, but novel platforms such as quadruped and multi-legged robots are gaining traction as capable exploration devices. In this context, [143] presented a method for exploration with motion efficiency using multi-legged robots such as a small hexapod platform (see Fig. 16). Their proposal uses the terrain traversal cost to estimate the best next goal. The traversal cost is estimated using the technique presented in [144], extended by the use of a robust bayesian committee machine (RBCM) inference mechanism with gaussian processes (GP) experts. The employed strategy greedily improves the traversal cost by navigating terrain that is considered unknown. The robot explores the spatial frontiers if the observed terrain is sufficiently known. This method allows the estimation of the variance for the knowledge about the terrain, guiding the platform to areas where knowledge can be improved. Dijkstra's algorithm is used for path planning for the nearest frontier. [145] also presents an accuracy analysis on terrain mapping with the same platform and Intel Realsense cameras (T265 and D435). In this mapping analysis, the height is estimated utilizing a Kalman filter with the sensor model on the cell heights. A threshold determines a traversable path on the height difference among neighbors of a cell. The experiments performed with the platform show that the T265 camera provides localization with a similar absolute error as the ORBSLAM2 [146] combined with D435 RGB-D camera but with less processing overhead.

Other 3D terrestrial exploration works use potential fields to navigate rugged terrain. In [147], the authors propose modeling exploration as a boundary-value problem (BVP) for uneven 3D terrain. The solution is computed over a 2D grid associated with an elevation map, and the robot can explore the environment while avoiding obstacles or other dangerous areas by following the gradient descent of the potential field.

5. Multi-robot exploration

Generally, with spatially distributed tasks, the exploration process can be sped up by utilizing multiple cooperative robots instead of a single robot. In this idea, a group of robots can distribute the perception acquired from the environment to generate shared maps and to pinpoint hazards or other essential features along the way.

Cooperation methodologies generally vary from centralized approaches, which are more straightforward but depend on good communication channels, to more complex cooperation methods, such as distributed and decentralized approaches that are robust to noisy communications. Coordination is the core of multi-robot systems and directly affects the performance of the overall task. Coordination could be static, where behavior conventions are adopted before performing a task, or dynamic, where the coordination behavior results from environmental changes and how this information is processed. The communication could also be implicit or explicit. Implicit communication means that robots obtain information as they perceive intentions and actions from other robots. For example, in [148], implicit communication is used in a team of robots to perform a box-carrying task in cooperation with only local sensor information. Many real-world robotic tasks could benefit from the agent's ability to interpret implicit environmental or behavioral clues, as we humans do so well [149]. On the other hand, explicit communication mechanisms are based upon the direct information exchange between agents, generally depending on dedicated onboard hardware to facilitate this. Most real-world robotic coordination strategies use explicit communication, with agents sharing position, sensor, or other environmental states. In this regard, [150] presented an

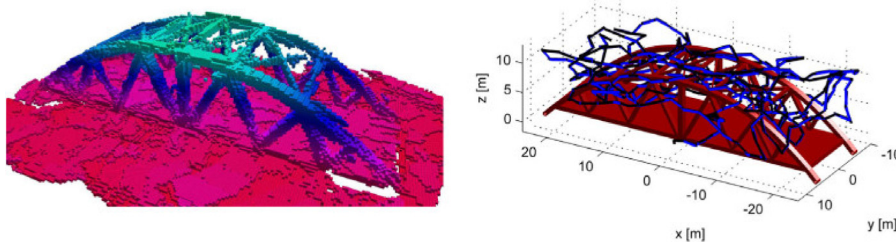
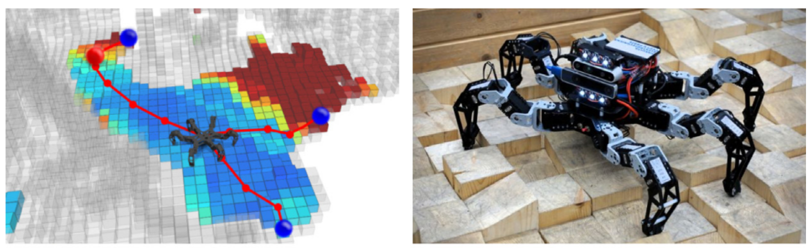


Fig. 15. Resulting map after exploring a simulated 3D bridge with a quadrotor using the receding horizon next-best-view planner. The ground truth with the exploration path (solid blue lines) and the robot odometry (black lines) are on the right. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Adapted from [125].



(a) (b)

Fig. 16. Terrain traversal exploration with a hexapod robot: (a) visualization of reasoning about possible navigational goals in the spatial frontier-based (blue spheres), and (b) real experiment in a controlled scenario.
Source: Adapted from [143].

in-depth analysis of popular coordination mechanisms typical for multi-robot systems. For specific exploration problems, maps can also be explicitly aligned online, directly at the exploration execution, or fused in a postprocessing step after the exploration is already finished.

Another common classification for multi-robot systems relies on the environment type, i.e., cooperative or competitive, or whether resource conflicts may occur. Approaches could consider the presence of noncooperative/competitive (defective or malicious) agents such as in [151,152]. Competitive behaviors occur when multiple robots compete to satisfy their own interests or in the presence of conflicting fitness functions inside the team [153]. Co-evolutionary approaches such as predator and prey and mutation-based algorithms can also be classified as competitive systems [154]. However, to the best of our knowledge, there is a limited amount of work on competitive exploration; the vast majority focuses on cooperation. This work assumes that the operational scenarios for exploration are free from malicious agents or other competitive environmental characteristics other than a shared frontier. A high-level classification of multi-robot systems can be observed in Fig. 17.

All techniques are limited by the type of robots available in a group and their capabilities. Considering this, multi-robot cooperation can then be classified into two extensive areas regarding the team capabilities: homogeneous and heterogeneous robot teams.

- **Homogeneous robot teams**: In this type of joint work, all robots share their most distinctive characteristics, such as wheels, approximate size, weight, and capabilities. Homogeneous teams can perform coordination or cooperation. Coordination allows performing a task more efficiently, although one robot can perform the task alone with a performance penalty. An example of coordination is patrolling; multiple patrol robots cover the environment faster than only one robot, but one robot can perform the task given enough time. On the other hand, cooperation allows fulfilling tasks that only one robot cannot perform while respecting the team's shared capabilities—for example, carrying a heavy object. A single robot cannot move a heavy object alone, but multiple robots sharing the same task can finish it.[3]
- **Heterogeneous robot teams**: In this type of joint work, robots do not share the same capabilities and can significantly diverge in locomotion modes, size, or weight. Some examples of robot collaboration are aerial/terrestrial, aerial/underwater, and quadruped/wheeled terrestrial robots. Collaboration allows performing tasks that a single robot type cannot.

5.1. Homogeneous coordinated and cooperative exploration

One of the first works in cooperative exploration is frontier-based exploration from [155]. In this proposal, the robots share perceptual information (local maps) with their peers when reaching a frontier but maintain separate global maps. Having separated global maps per robot allows the individual agents to make independent decisions about where to explore. A graph search algorithm over the grid extracts frontier paths, and reactive behaviors prevent collisions between robots, but there is no coordination for frontier selection or navigation. Centralized and perfect communication is assumed.

Colares et al. [156] proposed an improved frontier-based cooperative exploration methodology for ground robots where the utility cost of a normalized wavefront planner penalizes robots that go to the same frontier or near other robots. Map information is only shared with team members when the robots are close enough to acquire the relative position between them using planar markers. A map merger process uses the relative transformation between robots to add occupied and free cells to the robot's local map. [157] presents an approximation algorithm for multi-robot SLAM. The exploration problem is modeled as a multi-sensor active information acquisition in which both

3 https://robohub.org/coordination-cooperation-and-collaboration

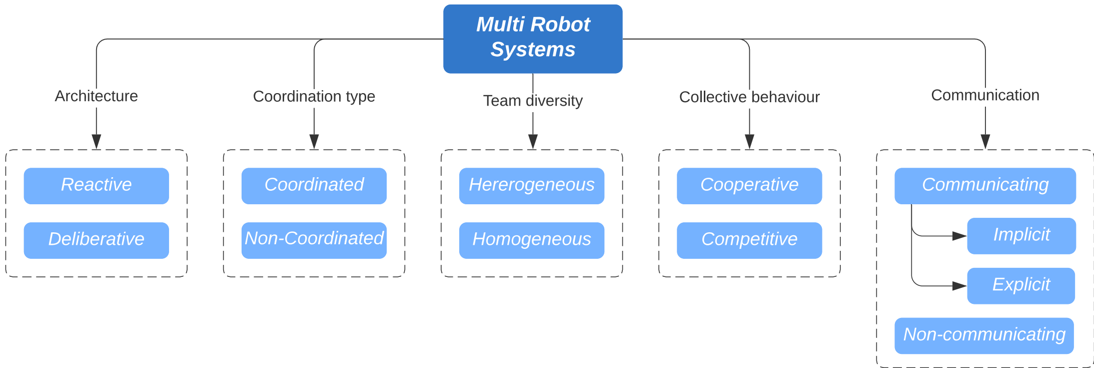


Fig. 17. Classification of multi-robot systems given architecture, communication, team diversity, collective behavior and communication type.
Source: Adapted from [153].

the sensors and the targets are treated as dynamic evolving systems. They proposed a two-step procedure featuring both non-greedy centralized and decentralized control coordination mechanisms. [158] proposes a frontier-based multi-robot exploration that segments the environment into Voronoi cells using the Manhattan distance of the robot positions. Robots are allocated to the nearest cell and have centralized communication to share information about their initial position, local map, and current status.

Regarding teams with limited visibility sensing and communication ranges, [159] presents a cooperative and decentralized coverage algorithm for unknown convex and concave two-dimensional areas. Robots share local information with neighboring robots within communication range. The coverage problem is modeled as a distributed constraint optimization problem (DCOP), and solved via a tailored max-sum algorithm using gradient descent with the objective of maximize the total sensing area of the robots.

A multi-robot cooperative reconstruction is presented in [160]. In this work, the task of performing a dense reconstruction of unknown indoor scenes is decomposed into smaller concurrent subtasks allocated to multiple robots, allowing the visitation of unknown areas simultaneously. The subtasks' target areas are modeled as a dynamic task assignment problem and computed using optimal mass transport (OMT). The optimal traverse path of each robot is generated by solving a traveling salesman problem (TSP), where each task view is visited exactly once. In this sense, other research has also modeled the optimal coverage problem with multiple mobile robots as an optimal task assignment problem with capacity constraints [161,162]. Premkumar et al. [163] propose an exploration method for orthogonal polygons with a team of robots. The proposal extends a single-robot polygon exploration algorithm to multiple simultaneous robots. A tree exploration algorithm is used for higher-level planning, and a sub-modular orienteering algorithm guides the lower-level planning.

Other techniques exploit the emergent behaviors of swarms to perform cooperative exploration. Swarm robots are generally simple, small, and inexpensive platforms with limited sensing and computing capabilities. In this sense, [164] proposes a cooperative and decentralized method for generating occupancy grids with a large group of swarm robots. The proposed method uses random walk for exploration, but the shared localization is estimated via pair-to-pair communication of their odometry, and the location uncertainty is reduced using a Kalman filter. The map is updated and merged using a Bayesian filter.

5.2. Heterogeneous collaborative exploration

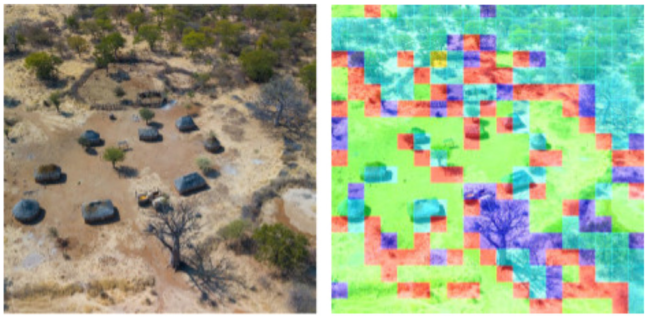
Heterogeneous teams allow the various capabilities of a robot team to overcome the limitations of a single agent. In this sense, a significant portion of state-of-the-art heterogeneous cooperation for exploration is performed using aerial–terrestrial collaboration. Since aerial and terrestrial robots have unique and distinctive capabilities, aerial platforms' power/battery limitations is compensated by terrestrial platforms' long endurance. The locomotion limitations of terrestrial robots can also be compensated by the privileged view and aerial platforms' holonomic kinematics.

Butzke et al. [165] presents an exploration method for aerial–terrestrial robots that deployed a UAV as a backup when a UGV encountered unreachable but explorable areas. Reachable and unreachable areas were estimated via ray-casting. The system is not entirely decentralized in this work, requiring a globally knowledgeable planner. The aerial path planner uses the DA* algorithm [166], and a more straightforward 2D planner is used for the terrestrial platform. [167,168] presented a frontier-based exploration that uses potential fields to guide the terrestrial robots to frontiers located on the ground. Motion primitives guide an aerial platform to the highest score frontier. There is no coordination mechanism other than the initial takeoff point in this work, and the communication is complete and perfect.

Maini et al. [169] presented an approach for persistent monitoring of 1.5D environments using a group of aerial robots with fuel constraints. The authors modeled the problem as an integer linear problem and formulated a set of rules for the mixed integer linear programming (MILP) solver that included "refueling stops". The refueling stops were defined by a terrestrial robots. Yu et al. [170] presented a cooperative coverage algorithm using a terrestrial and aerial robots. In this case, the autonomy limitations of the aerial robot are considered in the path planning and the terrestrial robot acts like a mobile charging station base. The proposed approach is based on boustrophedon cells, in which a tour with minimum coverage time is calculated. The problem was modeled as a generalized traveling salesperson problem (GTSP).

In [171], the authors propose a technique for aerial–terrestrial cooperation for hazardous environmental situations such as wildfires. The method classifies the textures of thermal and RGB aerial images acquired with a quadrotor, and those textures are used to assess drivable and nondrivable areas for a terrestrial robot. A gradient policy-based global planner drives the ground robot around the reachable terrain patches, and a convolutional neural network (CNN) estimates the local navigation behaviors (see Fig. 18).

A dense collaborative 3D reconstruction between aerial and terrestrial robots that uses UWB and visual inertial odometry for localization is presented in [172]. Robots maintain line-of-sight



(a) (b)

Fig. 18. Cooperative aerial–terrestrial exploration: (a) an aerial image of an open wild environment from a quadrotor, and (b) the same image after being processed by a textural classifier for terrestrial navigation.
Source: Adapted from [171].

between them to facilitate communication and localization in GPS-denied environments. The authors modeled the collaborative exploration as a dubins multiple traveling salesman problem with neighborhoods (DMTSPN), with the added visual constraints of the limited field of view (FoV) of ground robots (see Fig. 19).

6. Subterranean exploration

One of the first works in subterranean exploration using autonomous robots is presented in [173]. In this proposal, the authors show the inspection of an abandoned mine with a 1,500-pound custom-built terrestrial robot (see Fig. 20). Considering that the environment was flat and the robot had considerable size, traditional 2D navigation techniques allowed the robot to successfully transit the environment; nevertheless, most recent works consider a more detailed 3D environment representation to address the complexities of multi-level caves and overhang obstacles.

6.1. Terrestrial approaches

Terrestrial robots, being wheeled, tracked, or legged platforms, have considerable payload and battery autonomy advantages over aerial platforms, even though path planning and navigation is still a challenge for these types of devices on rugged and multi-level terrains. Recent hardware advances allow the purchase of commercial off-the-shelf quadruped robots. Although quadruped robots have particular locomotion complexities, these platforms are versatile, surpassing other terrestrial counterparts in many scenarios, such as climbing stairs or obstacle negotiation [61], and have sparked interest in novel locomotion, sensing and navigation methods applicable in confined spaces [174–176].

In [177] the authors present the Large-scale Autonomous Mapping and Positioning (LAMP) system, a LIDAR-based SLAM system for multiple terrestrial robots developed in the context of the DARPA Subterranean Challenge. The cooperative module uses a centralized base station that receives each robot's pose graphs within communication range and merges them into a shared pose graph, performing loop closures as needed. Experiments were performed in a cave environment with a team of wheeled ground robots (Husky A200). In an extension of previous works in 2.5D navigation, [178] presented a faster exploration framework for ground robots with a hybrid uniform grid-based and tree-based map representation. The tree structure enables fast access to neighboring cells and a low memory footprint. The frontier with the lowest traversable cost is selected for visitation using an iteration-bounded A* algorithm.

To generate terrain-aware safe exploration paths for wheeled robots, in [179] the 3D representation of the environment extracted from a LiDAR SLAM algorithm is modeled as a 3D mesh. The robot can reach the extracted frontiers from this mesh by generating safe, traversable paths using a linear combination of slope, energy consumption, and distance. The best frontier is selected through an information-theoretic approach, that estimates the most informative frontier after a virtual visitation using a LiDAR sensor model.

In [180], the authors propose a reactive bio-inspired exploration technique for corridor-like environments that uses a metric-topological graph map. In this proposal, horizontal depth scans generate a centering response for graph navigation, inspired by the optical flow present in various insect's visuomotor systems. The topological map is generated using image processing, and the robot iteratively explores the nearest unvisited node in the graph.

Legged and quadrupedal robots are gaining traction thanks to their extended mobility capabilities over traditional wheeled robots that improve terrain traversability and obstacle bypassing while maintaining a reasonable payload capacity, size, and endurance. In this vein, [181] presents an autonomy framework that enables mapping, odometry, navigation, and information-theoretic exploration with legged robots such as the Spot Mini from Boston Robotics (Fig. 21). Traversability maps are generated considering slopes and positive and negative obstacles. A cooperative quadruped exploration team is presented in [182], showing a distributed database mesh networking system for inter-robot communication. This work performs path planning by discretizing the LiDAR scan into a height map, and filtering out the ceiling. After estimating metrics such as the gradient of the map, rotation cost, distance cost, traversability cost, sidestep cost, and reversal cost, Dijkstra's algorithm is used over the configuration space to estimate the best path. The robots explore different areas of the environment using a set of initial commands from the operator, and the exploration behavior is frontier-based, leading a robot to the frontier closest to its current heading.

6.2. Aerial approaches

Due to their agility and speed, micro aerial vehicles (MAVs) are well suited for mapping 3D environments. The payload and autonomy limitations are partially overcome through current technological advances, allowing aerial robots to carry long-range LiDAR sensors, depth cameras, and powerful onboard processing capable of low-level and high-level decision making.

Aerial exploration methods such as the one proposed by [183] use a motion primitives-based path planning for agile exploration with aerial robots in confined spaces aiming for large-scale subterranean environments called MBPlanner. The method builds on top of Voxblox, a map representation capable of fast checking collision-free paths over an unoccupied known free space. Other works such as [184] uses receding horizon "Next-Best-View" planning (NBVP) with a Linear model predictive control (MPC) strategy for navigation in exploration missions in subterranean caves using multiple sensors, such as LiDAR, cameras, and IMUs. In [185] the authors overcome the memory usage of traditional grid and voxel map representations, using a gaussian mixture model (GMM) for perceptual modeling of the environment, creating a real-time occupancy reconstruction using GMM and LiDAR data obtained from a quadrotor. An information-theoretic approach to frontier selection selects the goals, and motion-primitives estimate the path planning. A GMM representation is compact and could be used with very-low bandwidth communication channels.

In [186,187], the authors proposed a local and global 3D exploration planner for UAVs in confined spaces that considers the

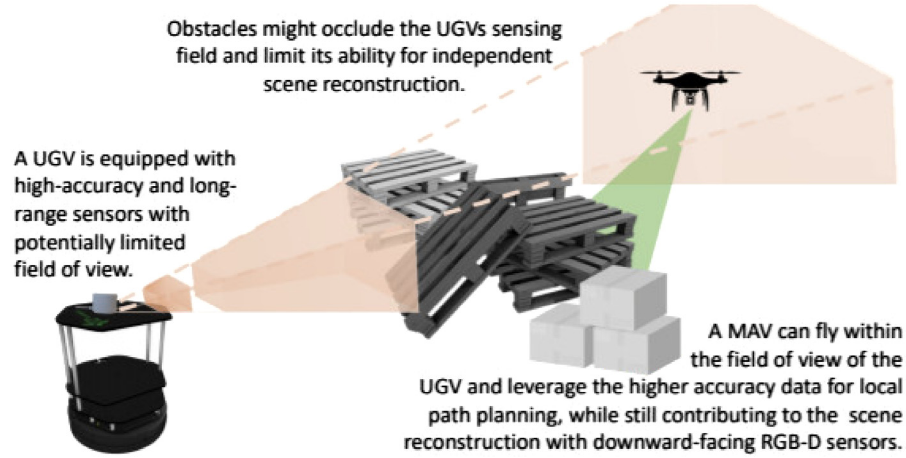


Fig. 19. Aerial/terrestrial UWB-based collaborative localization for sensing and dense scene reconstruction. *Source:* Adapted from [172].

(a) (b)

Fig. 20. Autonomous exploration in abandoned mines: (a) the Groundhog robot used for autonomous exploration, a 1,500-pound custom-built vehicle equipped with onboard computing, laser range sensing, gas and sinkage sensors, and video recording equipment. (b) The equipment entering the Bruceton Research Mine. *Source:* Adapted from [173].

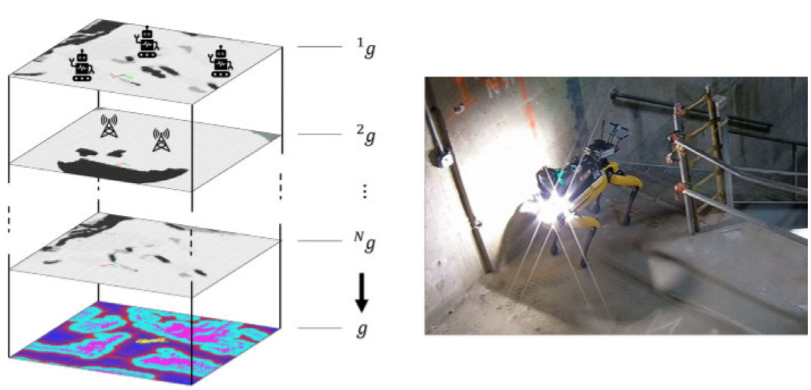


Fig. 21. A multi-layer traversability map for quadruped robots on the left and the Spot Mini robot during an exploration task on the right. *Source:* Adapted from [181].

volumetric gain of frontiers. The environment is modeled as a graph, and feasible paths are generated using the RRT* and Dijkstra algorithms. In [188], the authors proposed a 3D exploration method for confined spaces that uses ray-casting to detect flyable frontiers and a semantic classification for frontier selection. A fast UAV frontier-based exploration for large environments with narrow passages is presented in [189], where the output of an optimal grid-based planner is processed to increase the UAV distance from obstacles. An extended version of this work for large-scale caves, including an extension to multiple aerial robots, is presented in [190]. A 3D RRT* variant called Exploration-RRT is presented in [191], where the optimal trajectories to visit unexplored frontiers are selected using distance, the predicted dynamical model-based actuation costs, and the information gain of the unknown region.

Dang et al. [192] proposed a method for autonomous exploration and path planning in subterranean tunnel environments using a graph-based approach with an aerial robot (Fig. 22) called GBplanner. Their method used local and global planning, depending on the situation of the robot. Local planning uses a

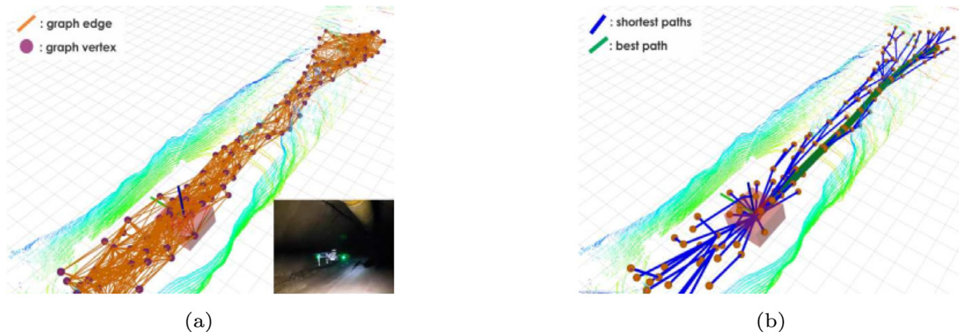


Fig. 22. Graph-based exploration path planner evaluation inside the TRJV gold mine in Winnemucca Nevada: (a) Local graph building, and (b) exploration gain evaluation.
Source: Adapted from [192].

rapidly-exploring random graph to find collision-free paths, and global planning is used for a return to home function. The exploration gain of a frontier is computed by the volumetric gain of each vertex combined with other weight functions related to distance and robot direction. Both local and global paths are estimated using Dijkstra's algorithm over the generated map graph. [193] shows a fast large-scale exploration for complex unstructured environments with aerial platforms, using an efficient hierarchical representation. A two-level framework guarantees efficiency by using a local planner with detailed data within a bounded window, and a global planner uses sparse data to generate coarse global paths that are then refined, producing kinodynamically feasible paths. The method optimizes the complete exploration rather than maximizing marginal greedy rewards. A real-time, kinodynamic planning and information-theoretic exploration framework for three-dimensional mapping of environments is proposed in [194]. This method allows the exploration of environments with complex concavities and disjointed objects. The method estimates the Cauchy–Schwarz quadratic mutual information (CSQMI) to explore the most informative regions. In [195], the authors present a pipeline for graph-based aerial exploration of cave environments, including system design, networking, software architecture, and sensing capabilities. The proposed approach uses the GBPlanner as a base for planning and the CompSLAM framework [196] for multi-modal mapping and localization.

A robust indoor aerial monitoring UAV system for constrained environments focused in search and rescue (SAR) operations is presented in [103], which was tested in the tunnel environments of the DARPA Subterranean Challenge. However, the proposed approach using 2D mapping is limited in fully 3D environments such as many subterranean confined environments.

Most aerial methods use rotary-wing platforms for exploration. In [197] the authors propose a novel and robust blimp-based exploration, merging autonomy, perception, mapping and localization into a lightweight platform with low power consumption and with an increased collision-tolerance.

Most methods for exploration use deliberative approaches, where the planning is carefully calculated before the actual robot motion. However, some works use reactive behaviors particularly for rapid obstacle avoidance. In [198] the authors propose a reactive, frontier-based exploration that uses both depth cameras and LiDAR. The LiDAR data are used for mapping and global planning over a euclidean signed distance field (ESDF) map representation. A set of multiple depth cameras allows avoiding obstacles using a reactive controller with APF, which has proven to be efficient enough for online avoidance of small obstacles without the need to stop the robot. In [199], the authors extended a previous bio-inspired proposal for ground exploration [180] for aerial platforms. This work uses a wide-field integration (WFI) framework with multi-line LiDAR data to produce a 3D centering response in cylinder-like environments. The proposal has been shown to be computationally efficient; However, it can be susceptible to local-minima in corners or split paths.

6.3. Heterogeneous multi-robot approaches

Recently, coordinated heterogeneous robot teams have won the top place in the DARPA Subterranean Challenge (2018–2021) in both virtual and real modalities. These results demonstrate that real-world deployments of heterogeneous robots are the core of feasible solutions to exploration problems, despite the design complexities of the coordination between multiple agents. Even more, considering the inherent networking and communication challenges of subterranean and confined spaces [200–202].

In this vein, the work of [203] addresses multi-robot cooperative exploration in GPS-denied planar (indoor) environments. The work presented an aerial platform equipped with a rotary LiDAR sensor and a depth camera, while a ground robot is equipped with a 3D LiDAR. The proposed exploration is frontier-based, with frontier importance estimated via volumetric gain. However, no detailed information about this procedure is available. Ground-based path planning is based on 2.5D height maps. Frontiers are chosen by solving an instance of the TSP problem, where the graph's costs are a function of information gain and traveling distance. The path planning is solved using batch informed trees (BIT*). The cooperation methodology is a simple two-step exploration procedure where the ground robot initially creates a coarse fast map, and then an aerial robot uses this map as a base to perform navigation using the denser rotary 3D sensor to generate a more detailed map.

In [204], the authors present an online frontier-based exploration algorithm that reduces the computational complexity of three-dimensional exploration and frontier analysis by modeling the boundary between the known free space and the unknown space instead of using dense volumetric representations. The algorithm extracts the frontiers from the point cloud using the visibility algorithm presented in [205] and estimates a convex hull of the point cloud. The proposed method uses ray-tracing only in a small subset of map points, thus reducing the overall complexity of an entire dense frontier extraction method. A compact representation of the frontiers is shared between the agents (mean and covariance of the frontier points, estimated reward, and observer location), and agents are penalized if passes through another agent's frontier. Frontier selection between ground agents is performed by selecting the frontier that provides the maximum reward per distance unit in a topometric map, and the aerial drones are launched near large novel spaces and thus navigate a frontier following a metric that considers the covariance, dimension of the frontier, and distance and current direction of the drone.

Graph-based path planning is common in recent cooperative and collaborative exploration research. The works of [126,192] present an extended version of their graph-based subterranean path planning algorithm called GBPlanner, compatible with aerial and legged robots (Fig. 23). The method uses a global and local planner architecture: an RRT or Dijkstra search for local interactions maximizes the informational gain while avoiding obstacles and respecting traversability constraints. For terrestrial robots, the planning is performed on a 2.5D map obtained from a front-facing depth camera [206]. A global planner creates a sparse global graph, used when the robots reach a dead-end. The volumetric gain is estimated using the sensors' parameters and ray-casting for the frontier nodes. The method was tested in real and simulated underground mine scenarios with the ANYmal legged platform and quadrotors. An extension of that research is presented in [207] using machine learning to perform path planning. By using the GBPlanner as a "training expert", the robot performs imitation learning on the expert data (DAGGER) with a deep learning network. A policy acquired from small LiDAR information windows can perform exploratory behaviors that reduce computational costs over the original training expert algorithm.

In [208], the authors presented a heterogeneous framework for exploration using aerial and legged platforms. The work proposes GBPlanner2, a graph-based exploration path planner used with the COHORT framework to allow coordinated multi-robot exploration. The method reduces the overall exploration time by estimating a fitness value for the frontier cells as a function of the number of robots approaching those cells. High-level mission planning is centralized, requiring a merge of the partial sub-maps before estimating the location of the best frontiers to visit. The method is resilient to communication problems and complex terrain, allowing long-term autonomy.

The complete NEBULA uncertainty-aware framework for exploration involving mapping and localization [209], data-fusion [210], navigation [181,211], LiDAR odometry [212], networking and deployable beacons [213], multi-modal loop closures [177,214,215], and artifact detection is presented in [216]. This framework can be applied to multiple robot types, particularly quadruped, wheeled, and quadrotor platforms. In this vein [217], presented a multi-robot decentralized framework for exploration and navigation, including a wide range of different platforms and a robust communication schema.

A complete system for multi-robot exploration is presented in [218], where robots autonomously share goal points and merge incremental sub-maps. The exploration approach is a graph and frontier-based path-planning algorithm using legged, wheeled, and aerial multi-rotor platforms. The connection between robots and the base station is a UDP-based mesh communication network created with beacons. The aerial platforms use the path-planning and reactive exploration methods described in [198].

6.4. Networked subterranean exploration

Heterogeneous exploration benefits from explicit communication. However, subterranean and confined environments typically pose severe communication constraints. These include the lack of existing communication infrastructure, naturally forming branches in the environment which challenge non-line-of-sight communication, electromagnetic interference from other electronics (e.g. mining equipment), and the high attenuation of radio signals over long distances. The authors of [219] provide an overview of wired and wireless communication technologies found in mines including Ethernet, through-the-Earth (TTE), WiMAX, RFID, etc. In addition, [220] surveyed wireless communication in mines including technologies, modeling, and implications of the environment.

Given that confined environments have few entrances/exits and are dangerous for human occupation, the data collected during exploration typically need to be transmitted to a remote (outside of the confined or subterranean environment) base. In this section we focus on the challenges imposed by this requirement.

Tethers made of optical fiber have been demonstrated as viable solutions to provide communication between an exploring robot and a remote base. The Axel rover is being designed to enter a vertical cave entrance into the lunar subsurface, and proposes the use of a tether for communications as well as power and mechanical support [221]. During the DARPA Subterranean Challenge, Team CERBERUS relied on a tether to provide communication to a wheeled robot, which then was equipped with a wireless interface for communication with other robots [222]. Tethers provide high-bandwidth, reliable communication but can typically only connect the base radio to a single robot, and severely restrict mobility of the tethered robot. Because of the flexibility and scalability of wireless communication, most practitioners of subterranean robotic exploration rely on wireless communication.

There is existing work on the use of wireless networks in subterranean spaces, and particularly wireless sensor networks which can also collect spatially distributed measurements in the environment. This is useful for monitoring, signal source detection, mapping, etc. The authors of [223] propose a mine communication system made up of wireless sensor networks. More recently, [224] presents a mine communication system using ZigBee as a wireless sensor network.

Wireless networks can provide the communication to enable multi-robot operations, however, wireless infrastructure may be unavailable or only partially available in underground and confined environments. In these cases, robots can be equipped with deployable communication repeaters or relay nodes. The key challenge is in optimal deployment of these nodes, since placing them too close together limits the effective communication range but placing them too far apart could allow the signal to attenuate too significantly between nodes. During the DARPA Subterranean Challenge, many teams relied on droppable communication nodes including 802.11 repeaters used by CERBERUS [222], Rajant breadcrumb nodes used by CSIRO [217], and Silvus software-defined radios used by CoSTAR [225,226].

In the absence of deployed nodes, robots can themselves act as a mobile ad hoc network (MANET). Peer-to-peer communication allows the robots to exchange partial maps, allocate tasks, and relay data to the base [227]. The key challenge is in maintaining connectivity. To address this, a framework for maintaining and improving the communication path between a stationary robot and an independently exploring robot, as shown in Fig. 24, is presented in [228]. A decentralized strategy for maintaining the overall connectivity of a group of robots is presented in [229]. In [230], the authors presented a controller that jointly optimizes sensing coverage and data routing to meet a constraint on communication rates.

Wi-FI and UWB were previously mentioned as sensors for localization. Robots can also use their radios (or additional UWB radios) to perform relative localization, using distance estimates based on the strength of received signals or time of arrival. In [231], the authors use the Received Signal Strength Indicator (RSSI) readings collected from messages exchanged between robots as a rough estimate of the inverse of distance, and use this relative localization to assist coordination. The authors of [44,232] present approaches to multi-robot localization in a shared frame via UWB-ranging between robots. When relying on radio frequency measurements for relative localization. Connectivity maintenance can be additionally constrained to minimize uncertainty in the resulting position estimates, as in [233–235].

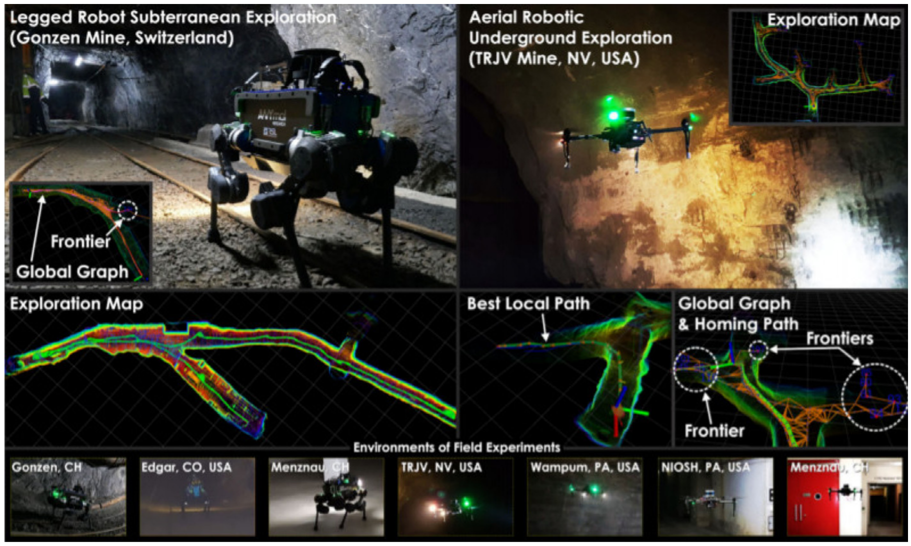


Fig. 23. Multiple instances of a graph-based exploration path planning in subterranean environments for legged and aerial robots.
Source: Adapted from [126].

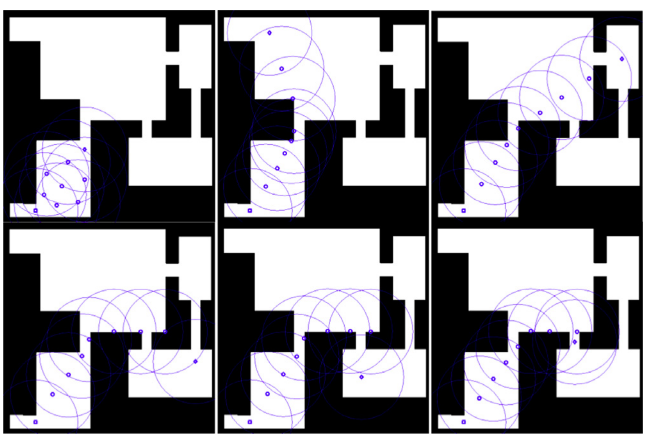


Fig. 24. Six snapshots of a robot team (shown in chronological order starting from the upper-left panel) seeking to maintain a connectivity chain given the communication radius shown.
Source: Adapted from [228].

Several works have considered the challenge of exploration under the constraint that data must be transferred to a base. The key challenge is that connectivity is at odds with coverage; exploring deep into a subterranean environment typically requires sacrificing connectivity with the base. Several approaches to restoring connectivity are explored in the literature, and a survey of communication-restricted multi-robot exploration is provided in [236]. Some take a periodic approach [237,238], other are rendezvous-based [239] or role-based and assign connectivity and exploration as distinct tasks [240,241], and others relay on the network metrics (signal-to-noise ratio, network congestion, data queue sizes) [226]. The authors of [242] introduced a recurrent connectivity strategy in which a connected deployment configuration is chosen and robots may lose connectivity enroute to the configuration. Exploration under a constraint on the time-average expected queueing delay, to ensure timely data transfer, is presented in [235]. In [243,244], the authors compare several exploration algorithms under different assumptions about the available communication model.

Communication for multi-robot systems has been well-explored by the academic community, but multi-robot operations in underground/confined environments typically still rely on static infrastructure (rather than peer-to-peer networking). Communication-aware exploration is a promising direction to complement uncertainty-aware exploration and traversability-aware exploration in subterranean environments.

6.5. Summary and insights

A summary of recent research in confined and subterranean exploration is shown in Table 3.

Real-word exploration uses a fusion of multiple approaches to estimate the location and importance of the next place to visit. Some works use a more direct approach for exploration considering tunnel-like scenarios, going directly to the frontier nearest to a robot's current heading. More deliberative approaches use graph-based and information-theoretic approaches. In particular, many works use the concept of entropy, volumetric information gain, and a sensor model to estimate the next-best view in the environment, and this view is selected for exploration. As subterranean and confined environments are complex, only a few works use 2D approaches, and those generally are aerial platforms capable of generating a "slice" of the complete 3D map for planning. Given the requirement of space efficiency, almost all works use a compact representation of the environment using voxels (Octrees, Quadtrees, and Euclidean Signed Distance Fields). A few use multiple map representations for different robot platforms, such as height maps for terrestrial robots and voxel-based maps for aerial platforms.

Recent research has shown that autonomous aerial platforms have a clear advantage over other types of platforms considering mobility: the advantage of not requiring interaction with the uneven and complex topography of most subterranean rugged environments is desirable for fast scouting. Moreover, with the current advances in hardware and onboard processing, drones can use a complete set of sensors such as depth cameras and LiDAR simultaneously, with local onboard processing capable of autonomous behavior. However, battery autonomy is still a challenge that should be addressed when designing these systems. In this regard, legged platforms are gaining traction given their increased mobility over wheeled platforms while maintaining sufficient battery autonomy and payload capacity. Only recently

Table 3
Summary of recent research on the autonomous exploration of confined and subterranean spaces.

Work ref.	Year	Exploration and autonomy criteria										Method description[a]
		Multi-robot	Wheeled/Tracks	Quadruped	Aerial	Two dim. (2D)	Elevation (2.5D)	Three dim. (3D)	Map type	Autonomy	Unreliable comms	
Terrestrial												
Azpúrua et al. [93]	2021	○	●	○	○	○	○	●	Mesh/Octree	●	○	Graph/information based.
Bayer et al. [178]	2020	○	●	○	○	○	●	○	Quadtree	●	○	Grid/Tree based exploration.
Bouman et al. [181]	2020	●	○	●	○	○	●	○	Voxblox/MLT	●	●	Graph/information based exploration.
Ebadi et al. [177]	2020	●	●	○	○	○	●	○	Point cloud	●	●	Graph-based cooperative SLAM.
Miller et al. [182]	2020	●	○	●	○	●	●	○	Height map	●	●	Frontier-based. Distributed mesh networking.
Ohradzansky et al. [180]	2020	○	●	○	○	●	○	○	Topological	●	○	Bio-inspired, metric-topological LiDAR map.
Aerial												
Ohradzansky et al. [199]	2022	○	○	○	●	○	○	●	Point cloid	●	○	Reactive bio-inspired, LiDAR map.
Ahmad et al. [198]	2021	○	○	○	●	○	○	●	Voxblox	●	●	Frontier-based exploration. Obstacle reactive.
Dharmadhikari et al. [195]	2021	○	○	○	●	○	○	●	Octomap	●	●	Graph/information based. Dijkstra. GBplanner and CompSLAM. Complete aerial system.
Kratky et al. [189]	2021	○	○	○	●	○	○	●	Octrees	●	●	Fast two-step grid-based exploration planner.
Lindqvist et al. [191]	2021	○	○	○	●	○	○	●	Voxels	●	●	Graph/frontier exploration. Multi-objective RRT.
Petravcek et al. [190]	2021	●	○	○	●	○	○	●	Octrees	●	●	Multi-robot grid-based exploration planner.
Tabib et al. [185]	2021	○	○	○	●	○	○	●	GMM	●	●	Information-based exploration. Robust comms.
Akbari et al. [188]	2020	○	○	○	●	○	○	●	Octomap	●	◐	Semantic graph/frontier based.
Dharmadhikari et al. [183]	2020	○	○	○	●	○	○	●	Voxblox	●	◐	Motion primitives/information based.
Petrlik et al. [103]	2020	○	○	○	●	●	○	○	Grid-map	●	●	Frontier-based exploration. A*.
Reinhart et al. [207]	2020	○	○	○	●	○	○	●	Octomap	●	–	Deep learning exploration path planning.
Dang et al. [186,187]	2019	○	○	○	●	○	○	●	Octomap	●	●	Graph/information based. RRT*. Dijkstra. GBplanner.
Huang et al. [197]	2019	○	○	○	●	○	○	●	Point Cloud	◐	◐	Blimp platform. PID tunnel following.
Papachristos et al. [184]	2019	○	○	○	●	○	○	●	Octomap	●	●	Receding Horizon. MPC.
Heterogeneous												
Agha et al. [216]	2021	●	●	●	●	●	●	●	Mixed	●	●	Graph/information based exploration. Autonomy pipeline. Breadcrumbs comms.
Cao et al. [193]	2021	○	●	○	●	○	○	●	Point cloud	●	●	Frontier/information based. Topological.
Hudson et al. [217]	2021	●	●	●	●	○	●	●	Mixed	●	●	Frontier-based. Watertight mesh. Hybrid A*
Kulkarni et al. [208]	2021	●	●	●	●	○	○	●	Voxblox	●	●	Graph/information based. GBPlanner2.
Ohradzansky et al. [218]	2021	●	●	○	●	●	○	●	Octree/Voxblox	●	●	Graph/frontier based exploration. Multi-robot autonomy pipeline.
Tranzatto et al. [222]	2021	●	●	●	●	○	●	●	Mixed	●	●	Exploration pipeline. Breadcrumbs comms.
Dang et al. [126]	2020	●	○	●	●	○	○	●	Octree/Voxblox	●	●	Graph/information based. RRT*. GBPlanner.
Williams et al. [204]	2020	●	●	○	●	○	○	●	Point Cloud	●	◐	Point-cloud visibility for frontier extraction and selection.
Qin et al. [203]	2019	●	●	●	●	○	●	●	Octomap	●	◐	Cooperative information/frontier based.

● = criterion fully covered; ◐ = partially covered criterion; ○ = non-covered criterion; "–" = no information available.
[a]Methods could use multiple techniques; this description highlights the most prominent exploration method per work.

commercially available, legged platforms can overcome obstacles, deal with uneven terrain and climb stairs in situations where other terrestrial platforms struggle. These types of platforms are a core part of many recent exploration approaches.

As seen in the bulk of recent works in autonomous exploration, most of them are directly or indirectly related to teams working on the DARPA Subterranean Challenge. In this sense, throughout the challenge, the teams showed off some of the most novel techniques for exploration in GPS-denied scenarios. The winning teams used heterogeneous robot teams for exploration, including approaches with wheeled, legged, and rotary-wing aerial platforms. Additionally, most of them created customized communication frameworks to deal with the lack of networking infrastructure in the explored environments, including inter-robot communication and wireless relay nodes.

The following are some of the lessons learned and open challenges in the autonomous exploration of confined and subterranean spaces:

Communication. Robust inter-robot communication and robot-to-base communication are particular challenges in subterranean environments. The lack of infrastructure requires the generation of mesh networks using the robots and other nodes, and these mobile networks have additional challenges. With a considerable number of nodes, there exists the need to design robust and efficient protocols that can limit and prioritize specific types of data over another, such as prioritizing a person's location over repeatedly sending a heavy point cloud map that can saturate the network. In these scenarios, the clever use of bandwidth is critical since bandwidth decreases with the addition of new nodes in a network. Many works use droppable nodes to increase the communication capabilities of the robots. Dropping communication nodes requires estimating the best location for dropping them and the mechanics to do so reliably. Additionally, since these droppable nodes will remain static after deployment, they can be used for localization by integrating them with UWB or other range estimators. Another challenge associated with dropped nodes is ensuring that mobile robots avoid damaging them. Tethered robots are not realistic, given the length and complexities of dealing with the cable tether.

Resiliency. For single robots, there should be sensor resiliency, using redundant sensors in critical applications with the reasoning capabilities of a consensus when one of them fails or shares misinformation. The prediction of problems is also a critical point for augmenting the robustness of platforms. Estimating when a component such as a motor will fail or if the battery is draining with an unexpected pattern can increase the overall mission autonomy by replacing the components before they fail in the field. A robot's internal software stack should also be projected and designed for resiliency: it needs to be robust enough to deal with sensor failures, reboots, communication network failures, path-planning problems, recovery behaviors, and other critical situations. Teams of cooperative robots should be designed to take over and replan if one or multiple platforms fail, a common situation in real-world exploration.

Multi-robot cooperation. The environmental situations found in confined and subterranean environments are too diverse for a single type of robotic platform to address, as observed in the DARPA Subterranean Challenge. Aerial platforms are particularly efficient for fast scouting and elevated environments, and ground robots can carry more sensors and perform other types of detailed assessments. Cooperation is critical to allocate different problems to the proper robotic platform and can also be used for allocating and distributing the computations of costly operations. Decentralized coordination mechanisms are needed in those cases where communication is unreliable. Map-merging is also a problem to address in multi-robot systems since drift and mapping errors can propagate to all robots. Human supervision could be highly beneficial given the complexities of cooperative exploration missions with multiple heterogeneous robots: detecting obvious map errors or resetting wrong position estimates, among other estimation problems. In this sense, those systems need to be designed to facilitate this human interaction with adequate interfaces and communication mechanisms.

Mapping and localization. Visual-SLAM techniques are widely used in many situations. However, occlusion, poor lighting, uneven brightness generated by the embedded LED systems, lack of textures, and fast movements can cause the loss of features and result in poor or inadequate localization. Many works use LiDAR to solve these problems, since RGBD cameras alone have shown limitations for large-scale exploration using their short-range and limited FoV. However, LiDAR also has limitations in environments with few geometric features and atmospheric situations as fog, rain, smoke, or dust. In this sense, combining multiple sensorial information (multi-modal sensor data) given the environmental situation is key to overcoming specific sensor limitations and generating more resilient and robust maps. For example, long corridors without features should rely more on the wheel and visual odometry than on LiDAR odometry. In this regard, the dynamic adaptation of the covariances of different sensors is an interesting challenge to address in future research. Another challenge in large scenarios is related to drift and loop closures, including the computational complexity of executing these expensive algorithms locally in the embedded robot computer. Another method to improve the localization of robots is to consider the semantics of the environment.

Navigation. Ground robots have evident mobility challenges in subterranean environments, where water, mud, stairs, and other obstacles can severely limit the exploration capabilities of those platforms. In this sense, safe and fast methods for traversability analysis are needed to locate places where robots cannot reach and safe areas where the chances of failure are low. However, a good topography and traversability estimation are closely related to the quality and detail of reconstructed 3D maps. Cooperation could be explored to improve navigation: more agile aerial platforms could quickly generate shallow maps to calculate an initial traversability estimate for their terrestrial counterparts. Water and mud can render many terrestrial locomotion mechanisms unfeasible, and detecting them reliably at a distance is still a challenge; however, different methods using the reflexiveness of LiDAR data or hyperspectral imaging could be interesting approaches for this.

Exploration methods. In practice, lightweight exploration algorithms that can compute the next place to visit quickly considering reachable and traversable paths are critical. In this sense, robots should be autonomous in most of the exploration missions since it will be commonplace for robots to be out of range of communication. Robots should automatically return to communication range to publish information when needed, such as when a person or object of interest is found or when a considerable new section of the map is explored. For real-world deployments of robots in subterranean and confined environments, frequent field testing is needed since many of the situations faced by the robots in exploration missions are difficult to reproduce in laboratory conditions, especially when dealing with coordinated multi-robot systems. Most works use heuristics to estimate the information or volumetric gain of visiting a frontier or choosing a specific path using a sensor model. However, it is difficult to reliably estimate what is behind an unvisited frontier; in this sense, developing methods to generate map extrapolations before calculating the volumetric gain of the frontier could greatly benefit the exploration process.

7. Conclusions

This work presented a survey on the autonomous exploration of confined and subterranean spaces. We described what defines a confined space and its challenges, both for human operators and robotic platforms. Confined spaces have several sensor limitations that restrict the operation of autonomous robotic platforms. We presented a description and classification of sensing techniques and devices for mapping and localization capable of operating in those environments.

A requirement for efficient exploration is the capacity of to represent already explored areas with a map and safely traverse the environment. In this sense, we presented some of the most popular map representations used in subterranean environments and methods for path planning, considering the terrain topography for terrestrial platforms and three-dimensional path planning for aerial platforms.

Regarding exploration, this work showed a taxonomy of exploration algorithms and an overview of methods for three-dimensional exploration using single and multi-robot approaches. In subterranean exploration, we presented a comprehensive analysis of recent works with aerial, terrestrial, and multi-robot approaches, including the requirements and challenges of the networking aspect of exploration. Finally, we presented a summary and lessons learned from these works and the DARPA Subterranean Challenge results. Our study concludes that despite the networking and coordination challenges that arise from the use of multi-robot systems, the results have shown that the use of heterogeneous platforms capable of coordinated work increases the resiliency and robustness of an exploration mission, allowing more detailed maps and increased understanding of the environment than with a single robot type. Heterogeneous and cooperative multi-robot teams are a clear trend in autonomous exploration. We expect this article to serve as a resource of recent advances in exploring GPS-denied scenarios such as subterranean and confined spaces for researchers and practitioners in the area.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Héctor Azpúrua is currently pursuing a Ph.D. in the Computer Vision and Robotics Laboratory (VeRLab) at the Department of Computer Science (DCC) of the Universidade Federal de Minas Gerais (UFMG) in Brazil and is an assistant researcher at the Instituto Tecnologico Vale (ITV). He has a bachelor's in Computer Science from Universidad Nueva Esparta (2011) and has an MSc in Robotics from UFMG (2015). His research interests includes Robotics, Artificial Intelligence, and Digital Security, emphasizing mobile robotics, machine learning, and real-time strategy games. He has worked in diverse research projects between academia and industry.

Maíra Saboia is a robotics technologist at NASA Jet Propulsion Laboratory with the Maritime and Multi-Agent Autonomy group. She was a post-doctoral researcher at NASA Jet Propulsion Laboratory as well as at Vale Institute of Technology (ITV) in Brazil. She completed her Ph.D in Computer Science and Engineering at University at Buffalo, State University of New York, USA, received her M.Sc. in Computer Science from the University of Campinas, Brazil and her B.Sc. in Computer Engineering from the University of Pernambuco, Brazil. Her research interests include multi-robot systems, field robotics, science autonomy and autonomous construction.

Gustavo M. Freitas received his B.Sc. degree in Control and Automation Engineering from the Universidade Federal de Santa Catarina and the M.Sc. and D.Sc. degrees in Control, Automation, and Robotics from the Universidade Federal do Rio de Janeiro, Brazil. His career has focused on robotics applied to environmental monitoring, agriculture, mining, and oil and gas production systems through his work at the Carnegie Mellon University - Field Robotics Center, the Petrobras Robotics Laboratory, and the Instituto Tecnologico Vale Robotics Laboratory, Brazil. Currently, Dr. Freitas is a professor at the Electrical Department (DEE) of the Universidade Federal de Minas Gerais, Brazil.

Lillian Clark is a Ph.D. candidate in the Autonomous Networks Research Group in the Ming Hsieh Department of Electrical and Computer Engineering at the University of Southern California. She received her B.S. in Aerospace Engineering from the Massachusetts Institute of Technology. Her research areas include multi-robot systems and sensor networks, with applications in harsh environment exploration.

Ali-akbar Agha-mohammadi is a Principal Investigator and Research Technologist at NASA's JPL and Caltech's Center for Autonomous Systems and Technologies (CAST). Dr. Agha's research centers on autonomy for robotic systems and spacecrafts, with a dual focus on planetary exploration and terrestrial applications. Dr. Agha led the Team CoSTAR and the development of the NeBula autonomy solution at JPL, which won the 2020 DARPA Challenge: Subterranean Urban Challenge. Previously, he was with Qualcomm Research, leading the perception efforts for self-flying drones and autonomous cars. Prior to that, Dr. Agha was a Postdoctoral Researcher at MIT. His research interests include artificial intelligence, autonomous decision making, and perception for robotic systems, with applications to drones, rovers, and legged robots. Dr. Agha was named a NASA NIAC fellow in 2018.

Gustavo Pessin got his D.Sc. in Computer Science at the University of Sao Paulo as a member of the Mobile Robotics Lab. During his D.Sc. Pessin carried out research within the Robotics Lab, at the Heriot-Watt University, Edinburgh, UK and the Communication and Distributed Systems Group, at the Universität Bern, Switzerland. In 2015, Pessin had a Visiting Scholar position within the Media Lab at the Massachusetts Institute of Technology. Currently, Pessin is an Full Researcher within the Robotics Lab, at the Vale Institute of Technology. The bulk of his research is related to intelligent systems and mobile robots.

Mario F. M. Campos, Ph.D., is a Professor of Computer Vision and Robotics in the Department of Computer Science at the Universidade Federal de Minas Gerais (UFMG), Belo Horizonte, Brazil. He holds B.S. degrees in Engineering, and M.S. in Computer Science, all from UFMG, and a Ph.D. in Computer and Information Science from the University of Pennsylvania, USA. His research interests include cooperative robotics, robot vision, sensor information processing, in which areas he has published over 250 papers in both qualified journals and conferences. He has supervised over 60 thesis and dissertations, and his main contributions are in haptics, multirobot cooperation, aerial robotics and robot vision. He is the founder of the Computer Vision and Robotics Lab – VeRLab, UFMG, Brazil. He has close collaboration with researchers from US and Europe sponsored by Brazilian and foreign agencies, and has been the PI and participated in several R&D projects with industry partners such as Petrobras, Vale, Engetron, LG Electronics, ABC Bull, and CEMIG. He has been a Distinguished Lecturer in the IEEE Robotics and Automation a member of the National Engineering Academy.

Douglas G. Macharet is an Associate Professor at the Department of Computer Science (DCC) of the Universidade Federal de Minas Gerais (UFMG). He received an M.Sc. and a Ph.D. degree in Computer Science from the same university in 2009 and 2013, respectively, and in 2019 he was a visiting researcher at the GRASP Laboratory at the University of Pennsylvania. He is with the Computer Vision and Robotics Laboratory (VeRLab), and his main research interests are in mobile robotics, considering topics such as motion planning and autonomous navigation; multi-robot systems and swarm robotics; and human-robot interaction.