Abstract: Subsurface networks include mining tunnels, caves, and the urban underground. Each of these environments presents a complex setting with significant challenges for exploration, remediation, exploitation, and so on. Multiple hazards may exist, communications are difficult, and conditions degrade and change over time. In most cases, this combination of challenges and hazards presents situations that are too risky for humans. Hence, a need for robotic solutions to operate when and where human risk is too high. To this end, we present a survey of research in autonomy, networking and mobility focused on exploring and/or mapping subsurface networks in unpredictable and unexplored environments. The focus is on mining tunnels as a proxy subterranean environment; motivated by the proximity of the authors to the Bonita Peak Mining District; a Superfund site consisting of 48 historic mines which have contaminated soil, groundwater and surface water with heavy metals as a result of historic practices. The exploration and assessment of the mining tunnels for remediation efforts presents an extremely challenging problem in subterranean navigation. Arguably, the environment in question is the most extreme and challenging subterranean environment. Unmanned assets must enter to explore and re-map the tunnels to assess safety for subsequent entrance by robots and/or humans for proper remediation. The survey is split into three categories — Locomotion, GPS-denied navigation and localization, and Communication. It is concluded with a proposed design for a platform that addresses the difficulties of exploring an abandoned mine.

1 Introduction

In our world today, there is a significant volume of underground infrastructure containing networks of mining tunnels, caves, and the urban underground (e.g. subway tunnels and underground shopping malls). Each of these environments presents a complex setting with significant challenges for exploration, remediation, exploitation, and so on. Multiple hazards may exist, communications are difficult, and conditions degrade and change over time. In most cases, this combination of challenges and hazards presents situations that are too risky for humans. Hence, a need for robotic solutions to operate when and where human risk is too high. To this end, we present a survey of research in autonomy, perception, networking, and mobility focused on exploring and/or mapping subterranean networks in unpredictable, and potentially unexplored, environments.

Exploration of these underground tunnels and passageways provides plentiful benefit. Abandoned mines pose danger to surrounding environments, where reclamation and environmental damage mitigation requires knowledge of mines before construction can be done. Rescue attempts in collapsed caves and mines pose great risk to first responders, a risk prominently posed by the lack of knowledge of the newly disturbed environment. Unmapped and flooded underground tunnel systems pose danger to above-ground infrastructure in the form of sink-holes and collapses; some of which could be predicted and/or prevented by a priori evaluation of the underground network. Even in urban settings, subway tunnels, sewer systems, and storm drains need constant inspection and exploration for operational health and safety regulations.

In this paper, we investigate current and potential modes of robotic exploration of subterranean environments, with a specific focus on mines and tunnels. The development of this work came with the intention of designing and developing a specialised platform for the exploration of abandoned mine tunnels in the Bonita Peak Mining District near Silverton, CO, USA. At the time of research, we found a lack of comprehensive surveys covering key technical aspects for addressing the problem. This paper is a result of our research, and the contribution is intended to provide a launching point for those interested in investigating this domain further. Broadly, this literature survey is split into three categories, (i) locomotion, (ii) GPS-denied navigation and localisation, and (iii) communication.

2 Motivation

Even when underground labyrinths, such as mines, have plans and previously-known layouts, these can dynamically change over time, rendering plans and maps obsolete. For mines, this includes corridor collapse, corridor flooding, poor air quality, acidic drainage in streams and pools, and so on. Thus, we must enter to explore and re-map the tunnels to assess safety for subsequent entrance by robots and/or humans for proper remediation.

The Bonita Peak Mining District in the San Juan Mountains is home to 48 historic mines, including the Gold King Mine (GKM) [1]. Since operation, the mines have been continuously leaking toxic water containing heavy metals and sediments into Mineral Creek and Cement Creek, both tributaries of the Animas River. In August 2015, the Environmental Protection Agency (EPA) was addressing the on-going leakage from the GKM, treating the mine water, and assessing the feasibility of further mine remediation [2]. During the assessment, pressurised water began leaking above the mine tunnel, causing it to give way and spill three-million gallons of concentrated, toxic mine waste into Cement Creek and ultimately, the Animas River. Though the mines of the Bonita Peak Mining District have been leaking steadily for decades, the toxicity, volume, and implications of this spill became a public concern.

The Bonita Peak Mining District was declared a Superfund site (this designation classifies land in the USA that has been contaminated by hazardous waste and materials which poses a risk to human health, and will receive federal funding for reclamation). Federal funding for reclamation will be used to treat the contaminated drainage in an immediate solution, and also focus on long-term solutions to the harmful environmental impact caused by the leakage.

Immediate efforts were taken to mitigate the damage inflicted on the surrounding environment and secure the GKM after the 2015 spill. Approximately three months after the incident,
unknown, and inaccessible nature of the mine. The extremely dark piles, strong wind gusts, and dripping water from the ceiling.

The extremely dark piles, strong wind gusts, and dripping water from the ceiling. The installation of a bulkhead, or concrete dam, which holds back several feet of thick sludge nearly 200 ft wide, between the top of the dam and the top of the mine corridor, would be key to achieving a long-term mitigation solution for the sludge, water (shallow over sludge and deep), uneven rocky ground, rock piles, strong wind gusts, and dripping water from the ceiling.

The GKM still steadily leaks, so the EPA and State of Colorado are exploring ways to mitigate the harmful effects of the drainage and remove heavy metals, such as lead, copper, arsenic, zinc, cadmium, and manganese, by routing the toxic runoff through retention ponds (e.g. see Figs. 1a and b). The first ~100 ft of the GKM has been reinforced to allow safe human entry (see Fig. 1c). Beyond this point, the geography, structural integrity, and air quality in the mine is unknown, and potentially hazardous to humans. Human exploration beyond this reinforced area is not permitted at all. Most areas beyond sight distance (see Fig. 1d) from the reinforced entrance to the GKM have not been seen or assessed in almost 40 years.

The GKM is not feasible and prohibited due to the conditions and unknown nature of the mine corridor. Since this is an area so restrictive for human exploration, an unmanned robotic platform was considered a viable solution for exploring deeper into the GKM to assess the feasibility of proposed remediation efforts. It was determined that creating a platform outfitted with sufficient data collection and navigation systems, and explaining why the use of a multi-modal vehicle must be necessary in this challenging environment. However, with the possibility of experiencing sudden terrain changes, development of a single solution for complete coverage of all subterranean environments may not be possible. This section discusses the current methods for locomotion in both single-modal and multi-modal robot locomotion.

3.1 Single-modal

3.1.1 Terrestrial: Many methods of locomotion have been developed using various designs to propel a vehicle over a terrestrial surface. Wheeled vehicles are common due to their high energy efficiency and simplicity. When a wheel is rolling, centripetal force reduces the required energy to keep the wheel in motion [3, 4].

The Numbat, shown in Fig. 3a, is an example of a wheeled vehicle used for subterranean applications. The Numbat was

IET Cyber-syst. Robot., 2020, Vol. 2 Iss. 1, pp. 1-13

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cameras to guide the operator. The Numbat is also equipped with
vehicle [6].

Fig. 3 Examples of single-modal, terrestrial robots
(a) Image of the Numbat [5], (b) Image of the Wolverine [5], (c) Image of the Hades vehicle [6]

developed by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) in 1998. The Numbat is a remotely-operated, eight wheeled, terrestrial robot that uses four cameras to guide the operator. The Numbat is also equipped with an on-board gas analysis package to determine the concentrations of hazardous gas in the underground atmospheres. However, the platform is large with base dimension of 2.5 m × 1.65 m and is operational in flat mines with no dams or blockages [5].

The Wolverine, shown in Fig. 3b, is an example of a tracked vehicle. The Wolverine was developed by Remotec as a bomb-squad robot, but was converted into a search-and-rescue robot by the Mine Safety and Health Administration (MSHA). This robot weighs over 1200 lbs and has explosion-proof motors that drive track treads. The Wolverine is also equipped with navigation and surveillance cameras, lighting, atmospheric detectors, night vision capability, two-way voice communication, and a manipulator arm. It also has a transmission range of up to 5000 ft. Although the transmission frequency of this robot is applicable for unexplored and abandoned underground mines, like the Numbat, it is too heavy to operate in muddy/sludgy environments and does not have the capability to climb over dams and blockages [5].

The HADES vehicle, shown in Fig. 3c, is an unconventional, terrestrial vehicle that was developed to climb over minor debris, while remaining small enough to fit between major debris such as machinery, collapsed beams, or wall/roof rubble. It uses ‘whegs’, which are spoked wheels that combine the reliability of wheels and the navigation capabilities of legs. They are capable of traversing through landscapes where traditional wheels would become trapped. It features wireless transmission, a sealed chassis, and a Kinect sensor to provide visual information in complete darkness. The platform, however, is low-profile and can only climb minor debris piles [6]. This platform also has not been tested in environments with deep sludge where it could get trapped and its sensors could become obstructed.

Although wheeled robots are energy efficient, they can be challenged by environments with rugged terrain or in regions where there is no hard ground (e.g. water-filled regions). Operational mines and clear tunnels are often ideal for wheeled locomotion; however, mines with unknown conditions, and those filled with water, may be unfit for wheeled traversal. These challenges have led developers to alternative terrestrial locomotion concepts such as bio-inspired designs. Bio-inspired locomotion classifies any form of movement that has been influenced by living things such as animals and insects. This type of locomotion has seen an evolving form for terrestrial locomotion in recent years [7–9]. Bio-inspired locomotion mechanisms will often involve jumping [10], walking [11], swimming [12], flying [13], and snake-like undulation [14].

The Scorpio, shown in Fig. 4a, is a bio-inspired design with multi-modal capabilities. It is inspired by the rare spider, Cebrennus rechenbergi. The design is lightweight and small in profile. It performs multiple modes of locomotion like walking, rolling and wall-climbing. However, it requires further development in transitioning between locomotion modes in response to different terrains. It also requires more development in the mechanism for transitioning between the floor and wall [7]. This design does not appear water-tight and lacks testing in wet, sludge-filled environments.

The GR Vision 60, shown in Fig. 4b, is being developed by Ghost Robotics as a mid-sized foldable tele-op and autonomous all-terrain ground drone built for security, safety, and asset inspection. This platform is supported by four legs and can have two-link manipulators. This platform allows for quick sensor swaps and can carry a max payload of up to 25 lbs [15]. To our knowledge, this platform has not been tested, so its utility in an underground environment is yet to be assessed and validated.

Another type of bio-inspired terrestrial robot that could potentially be used to explore abandoned mines are robots that use simple undulation locomotion. Simple undulation is a locomotion type that is not rigid enough to operate in mines filled with water, may be unfit for wheeled traversal. These challenges have led developers to alternative terrestrial locomotion concepts such as bio-inspired designs. Bio-inspired locomotion classifies any form of movement that has been influenced by living things such as animals and insects. This type of locomotion has seen an evolving form for terrestrial locomotion in recent years [7–9]. Bio-inspired locomotion mechanisms will often involve jumping [10], walking [11], swimming [12], flying [13], and snake-like undulation [14].

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ability to cross gaps or conform to rough terrain. Each segment has driven tracks on all four sides which prevents disruption of locomotion if it rolls over. This platform can be controlled without a tether but requires three operators to control deflection and stiffness in each pair of joints. Having multiple operations to perform resulted in issues coordinating control over new terrain types [16]. Additionally, the low profile of the robot would pose a concern for sensor blockage when navigating through thick sludge.

3.1.2 Aerial: Due to the unpredictable and rough terrain present in subterranean mines, specific situations may conclude that an optimal solution is to use unmanned aerial vehicles (UAVs), such as multicopters or blimps, to avoid conditions on the ground altogether. The predominate challenge for aerial vehicles is the relatively high power consumption, which leads to trade-off issues when optimising payload capacity versus flight time. These vehicles are also sensitive to wind conditions and movement through narrow spaces. This presents challenges in assessing its application to this environment. We remark that the platform must support enough payload to carry a sufficient sensor payload to ensure adequate data collection, and an external light source if any visual data are collected by that payload.

A Swarm of Micro Flying Robots (SFLY), shown in Fig. 6b, utilises the abilities of a swarm of multicopters that are capable of autonomous navigation and three-dimensional mapping. The use of multiple multirotors allows for optimal surveillance coverage in GPS-denied environments [19]. The major concern with multiple flying robots in confined spaces is the greater risk of one being blown into another by the periodic wind gust, or crashing in to each other. Either of these scenarios could ultimately result in many of the robots fatally crashing. Although, if the spacing between the robots is significant enough, this should not be a concern. The SFLY system could potentially be used to as a data mule system to relay information/controls/data through the tunnel or mine for a robust communication solution.

The iSTAR, shown in Fig. 7, was developed by the Georgia Institute of Technology for applications in researching control of underwater vehicles [22–24]. For a miniature blimp with a width of 60 cm and a length of 120 cm, the carrying capacity is 250 g when 600 m above sea level. At full speed, each of the four motors provide 20 g of thrust. The Blimpdrone platform was equipped with two CCD colour cameras to identify markers located in the research lab. Due to the lift provided by the helium balloon-like enclosure, the Blimpdrone has a significantly longer flight time than most multicopters, but a significantly limited payload capacity.

3.1.3 Aquatic: With pooled and flowing water common in mines, we examined aquatic vehicles for potential solutions. Autonomous underwater vehicles (AUVs) and autonomous surface vehicles have been used for survey and research missions in the past, see e.g. [26–29]. Aquatic locomotion is uncommon in subterranean environments because water levels are typically shallow [30] and inconsistent. This presents major challenges for operation of fully-submerged vehicles, but provides opportunity for light rafts which skim on the surface of water. Surface craft USVs have been used with human teleoperation [31]. Aquatic locomotion below the surface has been inspired by fish-like manoeuvres, e.g. [32]. However, all of these platforms require some depth of water in which to operate and locomote; this cannot be guaranteed throughout the mine environment.

The Heron, shown in Fig. 9, was developed by ClearPath Robotics. The dimensions are 1.35 m × 0.98 m × 0.32 m with a weight of 28 kg. The Heron has a max speed of about 1.7 m/s. The Heron can also come equipped with different cameras, GPS units, IMUs, and Laser range finders [33]. The geometry allows for submerged sensors to be mounted and sensors to be mounted above the water. The size and weight make this platform not ideal for the mine environment because of the muck and limited size dimensions.

The Ecomapper, shown in Fig. 10, was developed by YSI. The platform comes with temperature, conductivity, depth, and three axis digital compass sensors. It has an endurance of 8 h with a speed range of 1–4 knots [34]. The Ecomapper is an autonomous vehicle that is used mostly for water quality and mapping in the domain underneath the water. As mines rarely have contiguous water paths through them, a purely aquatic platform is not viable.
For our considered scenario, the UGV would have to be able to traverse deep sludge, common in flooded mines. After reaching an obstruction, the range of exploration would be limited to the flight time or umbilical tether of the UAV. The concept of combining two different modes of locomotion does provide a novel and reasonable approach.

The Flying Car, shown in Fig. 12, is a micro-aerial vehicle developed to efficiently explore varying terrains. This platform can save power by rolling through manageable terrain. When confronted by and obstacle, it can activate propellers to fly over the object and then continue on its wheels [35]. This platform will be presented with the same challenges as all of the other multi-rotor platforms; the balance between power consumption and payload capacity is no easy task.

The CSIR-CMERI, shown in Fig. 13, was created by the Central Mechanical Engineering Research Institution in 2013 [36]. It is an amphibious platform, which operates in terrestrial and aquatic conditions. It has continuous tracks (tank treads) that have been paired with thrusters that allow for exploration on land and underwater. The treads allow the vehicle to manoeuvre in muddy conditions. Although this vehicle can explore dry or fully-submerged mines, it is not designed to climb over dams or blockages [36].

4 GPS-denied navigation and localisation

When possible, the use of a global navigation satellite system, such as global positioning system (GPS), is a low-cost, accurate, and reliable tool for localisation. Many autonomous or operator-driven applications that use GPS must operate outdoors with access to an open sky, so that on-board radio receivers can connect to multiple satellites. This, unfortunately, is not the case with exploration of a subterranean environment. GPS loses all of its utility in environments like this, where receivers lose all line-of-sight with satellites. This problem is a heavily-researched area in mobile applications such as: indoors, underwater, disaster-stricken areas, built-environment corridors, and so on. This section will look at how the problems of navigation and localisation have been addressed in GPS-denied environments.

For a platform to effectively move from one location to another, plan routes, or make decisions while exploring an area, methods for navigation and localisation are required. This might be accomplished with a human operator having some level of control over the platform [e.g. manual (teleoperated) control or semi-autonomous assisted control] or a completely autonomous robot. Navigation requires sensor measurements from dead-reckoning and external environment sensor measurements, providing useful feedback to the operator or robot so they can safely avoid obstacles, build a map, plan optimal routes within the map, and ultimately reach a goal. Localisation also requires these sensor measurements, but uses them to help the operator or robot estimate where they are in the world relative to their current position or some coordinate frame origin [37].

4.1 Mapping

Without GPS, a map may act as a useful tool for planning an optimal route, avoiding known obstacles, and understanding where the platform is within the environment. This is a highly-researched area because of the many challenges that exist when trying to create a map for a given environment. These challenges include error caused from sensor noise accumulation, environmental complexity, correspondence of sensor measurements to previously recorded data points, dynamically changing environments, creating strategies to explore an environment to create a map, and strategies to navigate the map [38]. Once created, there are multiple ways to store and access the information contained within the map(s), e.g. feature maps, occupancy grids [37], or topological maps as seen in Fig. 14.

Feature maps represent an environment and obstacles in the environment as landmarks. The landmarks take the form of geometric shapes such as points and straight lines. For a platform to localise using a feature map, multiple landmarks must be recognised [42]. Since feature maps can use a sparse amount of objects, computational cost can be kept low. However, using...
feature maps can lead to issues with incorrectly associating measurements with points on the map [43]. Occupancy grids represent an environment as a grid representing areas in the environment that have a probability of being traversable or not. This method can use sensor measurements without the need of extracting features, but can be computationally expensive as the map becomes larger and more complex. A topological map represents an environment based on connected nodes containing information on location. Topological maps can represent large environments in a more abstract form holding only node and path information that are required. Topological representations can be weak when dealing with dynamic and cluttered environments and can fail to recognise when measurements are incorrectly associated with the environment. This is due to mainly using qualitative information instead of quantitative, or not implementing a distance metric on the topography [43].

4.1.1 Path-planning: Once a map is constructed, there are multiple ways to plan routes within that map. Some methods for planning include A* [44, 45], D* [46–48], probabilistic roadmap (PRM) [49, 50], and rapidly-exploring random tree (RRT) [51]. While the A* and D* algorithms find the lowest-cost path, they have high computational requirements which may hinder path-planning performance. The PRM algorithm and the RRT algorithm are both path-planning strategies that are low in computational requirements due to their use of a random, sparse sampling of the map to create a path. This allows them to produce path planning that is computationally efficient, but the path produced may not be optimal with regards to the underlying cost function. Below is a brief description of each of the aforementioned path-planning methods for environments with existing maps.

The A* Algorithm – A path-planning technique that uses heuristics to find the shortest path to a goal by examining all possible paths and using an estimation of the cost of path completion [52]. The A* algorithm will find the path with the lowest cost but is not adaptive to new information in the environment. The A* algorithm was chosen by Liao et al. [53] to create an optimal, collision-free path in an unknown forest environment.

The Dynamic A* algorithm – This algorithm is also known as the D* algorithm, is a variation of the A* algorithm that allows for fast, dynamic re-planning when changes in the environment are detected [37]. This replanning ability is added and added benefit to the lowest cost path. This is an important feature for situations where the environment may be represented by imperfect information [54], partially known [55], or containing dynamic obstacles [48].

PRM and RRT – Random, two-phase probabilistic path-planning methods consist of a planning phase and a query phase. The planning phase creates a random graph containing a node network of randomly generated points connected by paths that do not cross any known obstacles. The query phase traces a path from the starting node. This path travels through the neighbouring nodes until it reaches the node closest to the goal. To make changes to the path, only the query stage needs to be altered. The PRM planner does not make the most optimal path and can fail to discover routes through narrow areas or even fail to make a connected path if there are not enough generated points. The PRM planner does not take into account non-holonomic constraints of a platform. This is taken into account for with the RRT planner. Both [56, 57] use the PRM algorithm to generate collision free paths for UAVs. The solution in [51] used the RRT to generate paths around known, static obstacles and a reactive planner for detected obstacles.

4.2 Localisation techniques

4.2.1 State estimation: Noise accumulation in sensor measurements induces uncertainty in map creation, navigation, and localisation within an environment. Sensor drift accumulates over time, and sensor bias offsets actual measurements from reality. The use of recursive filters to resolve unbounded uncertainties has proven useful in addressing these challenges. Recursive filters are generally derivations of Baye’s rule, which is a method of updating a previously held prediction in light of new information and is described in the following equation:

\[ p(x_t | y_1:t) = \frac{p(y_t | x_t) p(x_t | y_1:t-1)}{p(y_t | y_1:t-1)} \]

IET Cyber-syst. Robot., 2020, Vol. 2 Iss. 1, pp. 1-13

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Fig. 9 Image of the Heron from the ClearPath Robotics web page [33]

Fig. 10 Image from the Ecomapper spec page [34]

Fig. 11 Diagram of the Marsupial platform created by Texas A&M [15]

Fig. 12 Flying Car [35]

Fig. 13 Amphibian subterraneus robot developed by CSIR-CMERI [36]
Bayesian filter that is commonly used in robotics [60–63]. The method (a.k.a. the particle filter) [59].

The Kalman filter provides an estimate of state by assuming that the sensor reading, a sensor reading [37]. Two common approaches for solving Baye’s filter for robot vision: a survey (a) to tweak the estimate. The error covariance is updated and the uncertainty in position measurements and noisy sensor data are zero-mean and Gaussian [37]. This filtering process consists of two parts: the prediction process and the measurement process.

The prediction process estimates the state and the error covariance of the state. The measurement process updates the position estimation using Kalman gain with sensor measurements to tweak the estimate. The error covariance is updated and the process is repeated with the updated measurements. The Kalman filter was created with the assumption of a linear system. The extended Kalman filter (EKF) was later formulated for the use in non-linear systems. There are more than 20 variations to the Kalman filter and the EKF that have been developed. More on the use of Kalman filters and their variations can be seen in [e.g., the particle filter] [59].

The Kalman filter – and its variations are examples of a ‘Bayesian’ filter that is commonly used in robotics [60–63]. The Kalman filter provides an estimate of state by assuming that the uncertainty in position measurements and noisy sensor data are zero-mean and Gaussian [37]. This filtering process consists of two parts: the prediction process and the measurement process.

The prediction process estimates the state and the error covariance of the state. The measurement process updates the position estimation using Kalman gain with sensor measurements to tweak the estimate. The error covariance is updated and the process is repeated with the updated measurements. The Kalman filter was created with the assumption of a linear system. The extended Kalman filter (EKF) was later formulated for the use in non-linear systems. There are more than 20 variations to the Kalman filter and the EKF that have been developed. More on the use of Kalman filters and their variations can be seen in [Kalman filter for robot vision: a survey] [64].

The Monte-Carlo method – is used when the error measurements cannot be modelled as zero-means and Gaussian [65–71]. It is also known as a particle filter because it represents the estimations of a robot’s state as a particle cloud. The estimate of state is updated as new sensor readings are taken. Particles that are more closely match the sensor readings survive consecutive samples while those that do not are eliminated [37].

4.2.2 Dead reckoning: Dead reckoning is a navigation method that depends on odometry and/or inertial navigation. By fusing measurements from an odometry source or an IMU with a compass, the speed, heading, and time of travel for a robot can be determined. Dead reckoning utilises a combination of incremental measurements to provide an update to the pose estimation of the robot, relative to a previously measured position/location.

Odometry – here we utilise angular rotation measurements of a rotational drive to determine linear displacement via kinematic equations. This technique is inexpensive and accurate over a short distance, but leads to a large accumulation of drift over long periods of time. Systematic errors such as unequal wheel diameter, wheel misalignment or finite encoder resolution, and non-systematic errors such as uneven terrain and wheel slippage, are the sources of this drift.

Inertial navigation systems (INS) – Inertial navigation systems utilise IMUs and gyroscopes. The IMU provides 3-D translational and rotational information, relative to a known measurement [72], which updates over time. INS are self-contained which means they operate using only gravity as an external reference. However, as measurements are successively integrated over time, large amounts of error accumulate and need to be reconciled [72, 73].

Both odometry and INS have advantages in dark/unlit environments, but to correct for the large accumulation of error, these systems are best improved when fused with data from additional sensors to correct or minimise the drift.

4.2.3 Beacon-based methods: Active beacons use either trilateration or triangulation with three or more beacons to provide the absolute position of a platform [74]. These devices consist of visual based [75], radio or Wi-Fi based [76–79], infrared (IR) based [80], light-based [81], and acoustic-based beacons [82–84]. There are a few exceptions that use a single beacon such as [85, 86]. Beacons provide very accurate localisation information but can only work in limited applications due to the fact that they must be installed in known areas of an environment. There are methods that address this problem of installation by utilising teams of robots that localise off of each other [15, 84].

The Millibot, shown in Fig. 15a, operates in teams of four or more leap frogging robots. The position of a moving robot is calculated using trilateration from measurements made by three stationary robots using IR and sonar sensors [84].
determine distance. Sonar range readings provide excellent information of occupied spaces [87, 88]. Sonar navigation creates an incremental global map of an unknown environment in great detail by tracking landmarks is an easier task than with natural landmarks. However, this method is less flexible than the use of natural landmarks because it is confined to locations where the landmarks have been manually placed [74].

4.2.5 Landmark-based methods: Navigation using natural or artificial landmarks takes advantage of distinct objects that have a fixed, known location relative to the robotic platform. The term ‘natural landmark’ refers to salient features that already exist in an environment and are not specific to robot navigation and localisation, e.g. corners or blobs [94]. When landmarks are used for localisation, visually distinct geometric features are found and matched with each other. Second, the scene geometry and camera poses are calculated using these features and are refined. Two of the common approaches to extracting features are blob detection [95–97] or corner detection [98–100]. The term ‘artificial landmark’ refers to distinct features that have been intentionally placed in the environment for the purpose of navigation and localisation. There are solutions that use simple geometric shapes [101] and patterns like QR codes [102, 103] and barcodes [104]. Since they are designed to be distinct and size and shape are known in advance, navigation and localisation using artificial landmarks is an easier task than with natural landmarks. However, this method is less flexible than the use of natural landmarks because it is confined to locations where the landmarks have been manually placed [74].

4.2.6 Visual-based methods: The conditions of the subterranean domain call for very robust methods for localisation. Recently, visual methods of estimating motion which rely on low-weight, low-powered, and inexpensive consumer-grade cameras have been developed. Some of the common camera types used are monocular [18, 105–108], stereo [109–111], hybrid [112, 113], or omnidirectional cameras [114–116].

Visual odometry (VO) and visual simultaneous localisation and mapping (VSLAM) are visual methods that work by collecting large sets of visual data which allow for estimating pose and reconstruction of the environment in great detail by tracking changes in pixel intensity or extracted features from consecutive image frames.

VO – this method incrementally estimates the ego-motion of a robot using images collected by a camera. It gets its name from the similarity it has to wheel odometry. Instead of estimating ego-motion by observing the angular rotation of wheel encoders, VO examines the incremental changes in sequential images from onboard cameras to estimate vehicular translation and rotation in real time and creates a local map [117]. A basic flowchart for the VO processing toolchain can be seen in Fig. 18, with detailed overviews presented in [89, 118, 119].

Simultaneous localisation and mapping (SLAM) – this method creates an incremental global map of an unknown environment while also localising the robot within that environment. SLAM was created specifically for applications where a robot will return to previously-visited locations in the environment. When this happens, a loop closure occurs, reducing the uncertainty in the map and sensor data and creating an accurate global map [118]. SLAM algorithms have been developed to use many different sensor configurations such as laser [120], sonar [121], IR [122], or a fusion of several sensors [123, 124]. As these sensors are often expensive and energy consuming, VSLAM algorithms have been developed to reduce these problems [19, 111, 123, 125–127]. VSLAM algorithms fall under two categories: filter-based and keyframe-based. Filter-based SLAM solutions rely on Bayesian filters such as the EKF [129] or the Monte-Carlo filter [130] for localisation and mapping with pose navigation.
connected and become the basis for the map. The map is then optimised using bundle-adjustment when loop closure is performed [105, 131].

Visual methods can be used on most robotic platforms such as UGVs [107, 132, 133], driverless cars [134], UAVs [18, 123, 126, 135, 136], and AUUVs [109, 137]. This is due to the fact that visual methods are not affected by the non-systematic errors that wheel odometry suffers from, making vehicle navigation more immune to rough and slippery terrain conditions. Errors in trajectory accuracy for VO range from 0.1 to 2%, which make it a reasonable replacement for GPS, wheel odometry, and other sensing systems used for localisation in the appropriate scenarios [118]. Visual methods often have high computational cost but there are solutions that are capable of real-time performance [110, 138, 139]. The largest caveat with visual methods are that they are very sensitive to operating and environmental conditions like lighting and texture which would limit their operation unless a sufficient source of illumination can be obtained [89]. However, the solutions used in [140, 141] address the problem of low-light by using binary descriptors.

### 4.3 Multi-sensor methods

Every type of sensor has strengths and weaknesses. Vision-based systems are sensitive to lighting conditions, laser and IR systems are sensitive to surface colour and transparency of an object, and dead-reckoning systems are sensitive to drift. Methods that fuse data from multiple sensor types can reduce the error obtained from relying on an individual sensor modality.

A multi-modal sensor fusion indoor/underground mapping being developed by MaXentric Technologies LLC [15]. This is a multi-modal system that fuses data from visual based sensors and time-of-flight based sensors for indoor and underground mapping. The combination of stereo imaging, laser, RF, acoustic, and optical sensor data helps to infer map features and resolve error in the output. Multi-modal sensor fusion indoor/underground mapping is wireless system with a high bandwidth communication and produces high-resolution images of the environment and objects within it. This system can be used as wearable hardware, or for autonomous robots [15].

The automated underground exploration (AUGERS), Reconnaissance and Surveying project being developed by Raytheon is exploring technology for mobility, data and networking, and perception and sensing a wide range of subterranean environments. The system uses a SLAM algorithm based on IMU, LiDAR, and image-based data fusion. This is assisted by an optical and UWB localisation that minimises dead-reckoning drift [15].

The I2NS image-inertial navigation system utilises a single camera with inertial measurements to provide position and orientation information without GPS. This technology allows for mapping indoor, outdoor, and subterranean environments with a drift of only 0.5%. The system has been proven effective for mapping a 7.45-mile route over 45 min with only 56.8 yards of drift [15].

### 5 Communication

Whether a robotic platform is operating autonomously or tele-operated, it is common to have some communication network for transmitting and receiving data between a robot and an operator. This connection provides the opportunity to see the current location or situation of the robot, or as backup for amassing collected data in the event that the autonomous platform is lost/damaged during the mission. The undesirable situation of a lost robot equates to the loss of any collected data that were not transmitted during the collection process. Unless a platform can explore, navigate, and return 100% independently, a communication network is effectively required to ensure data retrieval. This section discusses the options for communicating with robotic platforms during exploration of a variety of environments.

#### 5.1 Tethered

Long-distance signal propagation with wires provides a reliable signal strength and high-bandwidth connection without a direct line-of-sight. This provides an ideal communication solution for operation in clean, clear, open environments, but can have complications in unknown environments with obstacles that may snag or tear the tether. In underwater applications, a tether provides more resistance as the distance of exploration increases, as the additional length creates a larger surface area for frictional drag. This drag imparted resists the movement of the robot, and can be further compounded if the water current the robot is operating in opposes its desired trajectory. The drag or constant added weight due to the increase in length also effects terrestrial and aerial applications. The weight from a tether reduces payload and mobility of aerial robots, while drag and snagging is also common for terrestrial robots. A snagged or torn tether without a backup communication method can leave a robot stranded, potentially with critical data collected on-board.

#### 5.2 Radio

Communication via radio waves offers a broad range of frequency bands. Radio frequencies vary from 3 Hz to 3000 GHz and can be used for different applications [142]. The frequency range of 3–30 Hz is referred to as the extremely low frequency band and has been used in quantum mechanical applications [143]. The range between 300 MHz and 4 GHz is composed of the ultra-low frequency band, L, and S band. These frequencies are predominately used for communication [142]. Depending on the needs of a project, the frequency of a communication network can be decreased to increase the transmission range. Conceptually, this increases the power requirements and decreases the rate of data transmission. Independent of the frequency a signal is operating on, the signal quality will see degradation as the distance it is received increases [144]. It should be noted that observed signal propagation characteristics in different GPS-denied environments do not hold true when compared to subterranean operation [144]. There has been significant research in testing signal propagation models of radio communication in indoor environments such as offices and warehouses, and the root mean square (RMS) delay spread has shown no significant correlation with the distance between the transmitter and receiver in underground mine tunnels [144]. The RMS delay spread has been estimated to fall between 20 and 300 ns in environments such as office buildings and factories [145]. With a small RMS delay, utilisation of radio waves for communication shows promise. When the signal becomes weak due to interference – physical or otherwise – repeater beacons can be an invaluable asset when signal propagation suffers.

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**Fig. 18** Block diagram of the main components of VO [118]
The wave relay: mobile ad hoc networks (MANET) product line, shown in Fig. 19, was developed by Persistent Systems to allow for communication infrastructure development where traditional methods fail.

A new state-of-the-art radio module called the ‘embedded module’, developed by Persistent Systems has an HD video encoder and Android computer on-board. The computer allows for algorithms to run directly on-board. The module is 2 × 3.29 × 0.59 in and weighs 3.2 oz. The frequency module is interchangeable and there are currently three different modules. The S-band (2200–2500 MHz), the L-band (1350–1390 MHz), and the C-band (4400–5000 MHz). The embedded module claims to communicate more data further, quicker and more reliably [15, 146].

5.3 Through-the-earth (TTE)

TTE communication utilises ultra-low frequency electromagnetic signals (3000–8000 Hz) and can be categorised by three methods: surface-to-underground, underground-to-underground, and underground-to-surface. Recent testing includes test conducted at an underground coal mine located in eastern Kentucky in 2015. The antenna used was 120 m long or about 400 ft [147]. The primary challenge for TTE is the consideration of electromagnetic and radio signal loss through solid strata. Due to these variances, the functional range for communication can change significantly in differing landscapes [147]. Some mines have shown close to theoretical ideals in communication patterns while others show much weaker connections. At this point, the only way to be certain that TTE will function in a given subterranean environment would be to test in that particular subterranean environment. However, due to the 120 m antenna required it does not seem feasible to use TTE on-board a roving robotic platform, but shows potential for communicating to a base station built at a fixed location within a subterranean environment.

Digital magnetic induction network connectivity/positioning technology is a TTE transmitter by Vital Alert which uses technology developed at Los Alamos Labs. This technology is capable of transmitting text and sensor data ~400 m into caves. The compact, lightweight transmitter has been targeted for mine rescues and communications into subterranean operations [15]. The small transmitter is ideal for applications when payload is a consideration. A transmission distance of 400 m in caves is greater than the conventional off-the-shelf transmitter distances (Fig. 20).

6 Conclusion

In this paper, we presented a survey of existing solutions that could be used for applications in subterranean exploration of mines. Here, we used the complex scenario of an abandoned mine in the Bonita Peak Mining District in Colorado, USA to motivate the focus of the investigation. Three separate categories of interest were identified and examined: (i) locomotion, (ii) GPS-denied navigation and localisation, and (iii) communication. Locomotion was further divided into single-modal and multi-modal transport platforms. In the design space for single-modal locomotion, platforms that specialised in terrestrial, aerial, and marine travel were explored. The terrestrial platforms ranged from wheeled platforms to quadrupedal walking robots to snake like undulation based robots. The wheeled platforms were found to be efficient and simple, but challenged by extreme terrain. The bio-inspired robots had manoeuvrability at the cost of complexity and difficulty of operation and implementation. The aerial platforms used for subterranean exploration largely consist of multi-rotor drones, either operating as a single entity or as a network. These aerial platforms boast the greatest resistance to extreme terrain, but fall victim to air conditions and exceedingly short operation times. Since many mines considered in the motivating research contain water drainage and backup, aquatic platforms that were not designed with mine exploration were considered; though utility offered by the boat or submarine platforms was limited due to the lack of consistent traversable water in most mines. With the nature of most mines, it was found that single-modal marine or terrestrial platforms simply lack the necessary adaptability required in real-life mine scenarios, but offer constituents for multi-modal robots. A number of such potential multi-modal platform combinations already exist in the design space; most consisting of single platforms with combined propulsion systems, while others use a multi-stage approach with separate dependent platforms that cooperate.

Mines and other subterranean structures also pose difficulty on the control side of the robot; commonly relied on GPS localisation solutions are unavailable, and information transmission is similarly inhibited. To explore solutions to this, GPS-denied navigation and localisation along with communication were explored in the second half of this paper. Without GPS to supply a global reference, a robot must define a map of its environment with which to localise itself. Mapping and route planning are already well-explored fields, and as such, were only briefly covered as a preamble to localisation in a GPS-denied environment. Localisation without GPS has several options, all based on the use of multiple sensors to achieve an accurate pose estimate. Examples of such explored methods are dead reckoning, beacon-based, landmark-based, and visual-based localisation. These methods can also be used in tandem and fused to get an even more accurate reading on pose.

This paper finishes the survey with an investigation of communication from the robot to the outside of the mine. For the same reason that localisation needs to be done on the robot without GPS, data transferred from the robot to the operator is limited. The options for communication are limited to tethers, low frequency radio, and TTE communication. Tethers can both relay information and power, but are subject to physical limitations such as snaggling and drag. TTE communication utilises ultra-low frequency electromagnetic signals to penetrate the ground, offering substantial ranges. However, this method requires use of antennae that are far too large to implement on an exploratory robot. Low-frequency radio offers convenience of wireless communication; however its range can quickly be limited by obstructions underground; making relays and other infrastructure necessary to implement radio communication for any structures that do not offer constant line of sight.
Based on the information gathered for this survey paper, a prototype platform was developed and deployed into the GKM Superfund site in the Bonita Peak Mining District. In this instance, we produced a platform that could negotiate the extreme terrain while gathering visual data of the single-corridor mine shaft. Our 6 × 6 buoyant crawler platform (see Fig. 21) was designed to handle a large payload (~10 kg) while successfully negotiating the terrain of the GKM. Six buoyant wheels provide the platform with highpayload capability in water, sludge, and over rocky terrain. Independent steering control on the front, middle, and rear wheels allow for extreme manoeuvrability for overcoming a range of obstacles. The platform is tele-operated, and sends data over a 1.3 GHz communication channel. This is an example of the unique combination of capabilities required to achieve a successful robotic deployment in a specific subterranean domain.

7 Acknowledgment

This work was primarily supported by a grant from the State of Colorado, Division of Reclamation, Mining and Safety and the Bureau of Land Management. Additional support was also provided by NSF MRI 1531322 and Office of Naval Research Award N000141612634.

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