Special Issue: DARPA Subterranean (SubT) Challenge

Regular Article

Teleoperation for Urban Search and Rescue Applications

Jason T. Isaacs[1], Kevin Knoedler[2], Andrew Herdering[3], Mishell Beylik[3] and Hugo Quintero[3]
[1]Department of Computer Science, California State University Channel Islands, Camarillo, CA 93012
[2]Coordinated Robotics, Newbury Park, CA 91320
[3]California State University Channel Islands, Camarillo, CA 93012

Abstract: An important application of field robotics research is robotic assistance for search and rescue operations. The problem of robotic search and rescue requires techniques to map, navigate, and search unknown complex environments. In subterranean domains such as tunnels, caves, and underground urban environments these activities are made more difficult due to communication constraints and unavailability of global positioning systems. We present here Coordinated Robotics participation in the Urban Circuit of the Defense Advanced Research Projects Agency (DARPA) Subterranean Challenge which addresses these problems in the underground urban environment. Our Teleoperation strategy serves as a baseline approach by which to compare autonomous solutions. Our aim is to provide insight into our system design and our lessons learned from the competition.

Keywords: subterranean robotics, emergency response, teleoperation

1. Introduction

Mobile robots are increasingly relied upon in applications where human presence may be dangerous or laborious. One such application is search and rescue in structures that have become unstable due to damage from natural or manmade causes. For a robot to autonomously operate in such an environment, there are four key difficulties that must be considered: (1) mobility, (2) networking, (3) perception, and (4) autonomy (Defense Advanced Research Projects Agency, 2020). First, the robot must possess the mobility required to traverse uncertain and complex terrain including vertical passages and drops, nonuniform obstacles, and steep slopes. Second, the robot must maintain a communication network to receive commands from and communicate measurements to a base-station and other robots. In addition to mobility and networking, autonomous robots must be able to reason about their environments based on sensor measurements and make decisions about future actions through perception and autonomy.

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Correspondence: Jason T. Isaacs, Department of Computer Science, California State University Channel Islands, Camarillo, CA 93012, Email: Jason.Isaacs@csuci.edu

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We present our entry in Defense Advanced Research Projects Agency (DARPA) Subterranean (SubT) Challenge Urban Circuit. The SubT Challenge is a multistage robotics competition designed to stimulate research and innovations in the areas of mapping, navigation, and search in complex underground environments such as tunnels, underground urban environments, and natural cave systems. The Systems Track of the SubT Urban Circuit phase of the competition was held at the Satsop Business Park in Elma, Washington on February 18–27, 2020. The event took place in the reactor building of the nearly finished nuclear power plant, which presented unique challenges related to mobility and communication. The objective of the competition was to explore the complex environment in search of prespecified artifacts while maintaining a localization reference.

During the SubT Challenge, each team is given 1 h to find 20 artifacts in the subterranean environment. These artifacts represent survivors and other gear that may be associated with them. At the SubT Urban Circuit, these items were mannequins (representing survivors), cell phones (playing a video and emitting bluetooth/wifi signals), elevated CO2 levels (representing a gas leak or other hazard), backpacks (as might be carried by survivors), and air vents. Reaching and finding the artifacts was made more difficult by the presence of rubble, fog machines (representing smoke), stairs, and vertical shafts. To score points teams had to correctly identify the artifacts and report their position with less than a 5-m error (Defense Advanced Research Projects Agency, 2019).

The SubT Challenge is the latest in a long history of competitions hosted by DARPA to accelerate innovation in strategic areas related to autonomous robotics. Initially, the DARPA Grand Challenge (Thrun et al., 2006), (Urmson et al., 2006) and the follow-on DARPA Urban Challenge (Montemerlo et al., 2008) helped to stimulate a new era of autonomous vehicle innovation that has taken place in the nearly two decades since the first competition. While the more recent DARPA Robotics Challenge has helped to advance research in humanoid robotics (Atkeson et al., 2016), (Krotkov et al., 2017), (Karumanchi et al., 2017). Likewise, the SubT challenge has already resulted in many advances in the areas of autonomous underground search (Ebadi et al., 2020) and (Petrlík et al., 2020). Teams competing in the first two circuits of the SubT Challenge (Tunnel Circuit and Urban Circuit) deployed heterogeneous teams of robots to address the complex challenges presented by the subterranean environment. Most teams deployed one or more ground vehicles, many of which were wheeled robots such as Husky by Clearpath, while others deployed tracked vehicles (Williams et al., 2020), (Rouček et al., 2019) or walking robots such as ANYmal (Dang et al., 2020) or Spot Mini from Boston Dynamics (Bouman et al., 2020). In addition to ground vehicles, most teams included aerial vehicles in the form of multirotors (Williams et al., 2020), (Dang et al., 2020), (Rouček et al., 2019), and one team included a dirigible (Huang et al., 2019). To the best of our knowledge, we were the only team to deploy an Ackermann steer robot in either circuit of the competition.

We made the decision to use a teleoperation strategy. This decision allowed our team to focus on the mobility and networking difficulties associated with this complex problem domain while allowing our human operator to handle the tasks traditionally associated with autonomy and perception algorithms. This strategy comes with pros and cons. The primary contribution of this paper is the presentation of a baseline teleoperation strategy for rapid subterranean exploration, mapping, and search. We discuss the trade-offs of such a strategy and provide a baseline level of performance for other autonomous approaches to compare.

The remainder of this paper is organized in the following manner. In Section 2, we describe the various robotic platforms and sensor packages used in the competition. Section 3 presents the software used to perform Simultaneous Localization and Mapping, Autonomy, Communication, and Object Recognition tasks. Our approach to Teleoperation is explained in Section 4. Next, the system performance in the DARPA Urban Circuit competition is discussed in Section 5. Finally, lessons learned and future work are covered in Section 6.

2. The Robots

During the Urban Circuit, we relied on a blend of both aerial and ground platforms of various sizes, as shown in Figure 1. The robotic team consisted of a total of four ground platforms and eight

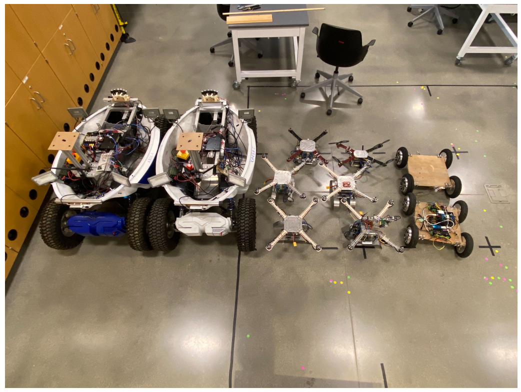
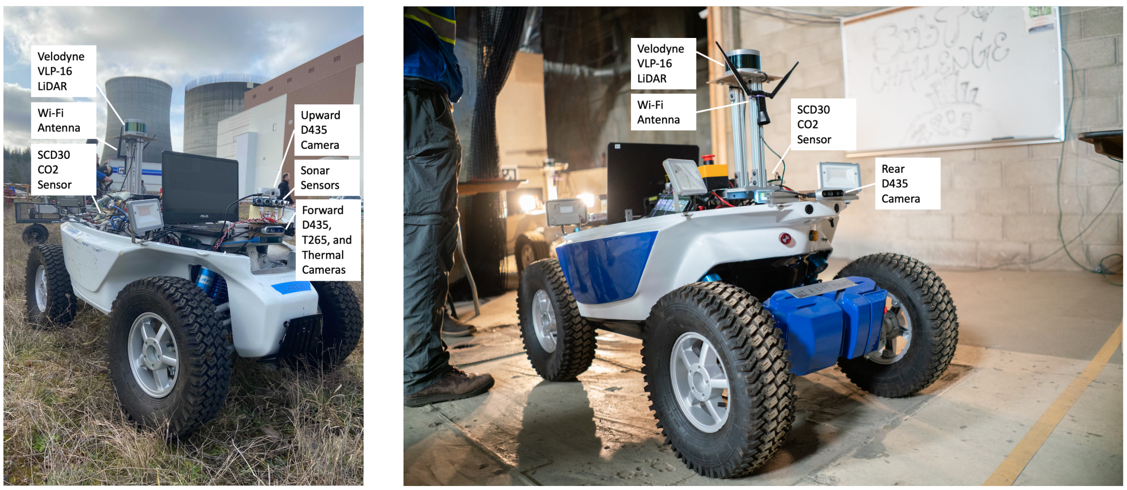


Figure 1. The team of robots partially disassembled in preparation for shipping.



(a) Karen front view.

(b) Rick rear view.

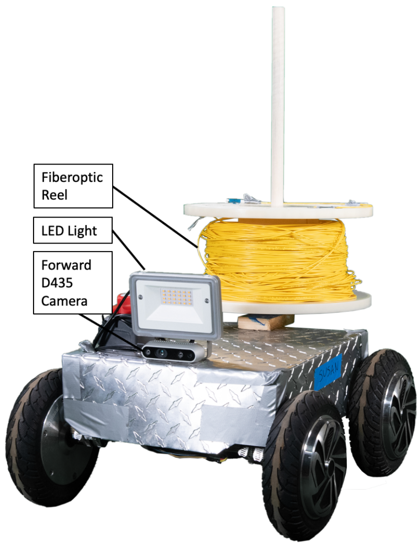
Figure 2. Ackermann Steer Ground Vehicle with annotations for sensor locations.

drones. This setup stemmed from the thought that when the ground vehicles cannot physically search an area, the aerial vehicles will instead be deployed. Another interesting decision we made was that each platform had a unique and memorable name clearly marked on the outside of it. Although this can be seen as a playful addition to our platforms, it also proved to be a helpful tool to be able to easily identify the platforms both physically and in the software.

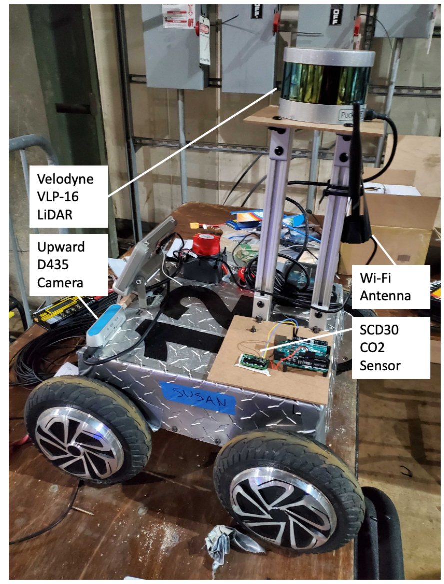
2.1. Ground Platforms

2.1.1. Large Ackermann Steer Platforms

Our two larger platforms, Karen and Rick, Figures 2a and 2b, were repurposed S series robots from SMP Robotics (SMP Robotics, 2020). These platforms were chosen for their high ground clearance (14 cm), payload capacity, and relatively fast top speed (4 km/h). The platforms were among the larger ground vehicles that still fit the competition´s size constraint, with a length of approximately 1.42 m and a width of approximately 0.78 m. The vehicles are equipped with a suspension system that allows the vehicle to traverse uneven terrain while keeping sensing payloads stabilized. The turning radius of the vehicle is approximately 5 m, which limited the maneuverability of the robot as compared to large differential drive robots fielded by other teams.



(a) Jeanine with fiberoptic reel and forward D435 camera.



(b) Susan annotated to show sensor locations.

Figure 3. Small Skid-steer robots used for searching small corridors and dispensing fiberoptic communication cable.

Although originally autonomous security robots, we stripped them down only leaving motors and chassis. From there a RoboClaw 2×60 A Motor Controller was installed for its native support of Ackermann steering and existing Robot Operating System (ROS) compatible nodes. Our onboard computer was an ASUS laptop (Intel i5-9300H, Nvidia GTX1650) as its included GPU and screen seemed advantageous to us for onboard object identification and debugging, respectively. The laptop was powered from a 24 to 120 V inverter positioned at the rear of the platform. Two Intel RealSense™ D435 depth cameras were installed on the front, one with a forward view and another with a view of the ceiling. In addition to D435 depth cameras, one additional Intel RealSense™ Tracking Camera T265 was placed with a forward view, and three HC-SR04 ultrasonic distance sensors were also installed. Near the center and at the highest point of the platform, a Velodyne VLP-16 LIDAR was positioned to provide an uninterrupted view of its surroundings. One last D435 depth camera was positioned at the back of the platform giving a rear view.

2.1.2. Small Skid-steer Platforms

The two smaller ground platforms, named Jeanine and Susan, Figures 3a and 3b, relied on three phase O-Drive motor controllers to drive four hoverboard motors. The bottom panel was a 13 inch square of three-quarter inch plywood with the hoverboard motors being attached with hose clamps. The Intel NUC mini PC and battery were secured with cable ties. We used Gigabyte GB-BXi7-4770R (Intel i7-4770R) NUCs running Ubuntu 18.04 and ROS Melodic. The side and top panels were a single piece of aluminum diamond plate cut and bent into a square box. On the top panels an LED light, e-stop, and single Intel RealSense™ D435 depth camera were attached.

Jeanine was equipped with a custom fiber optic cable dispenser. This apparatus consisted of a three-quarter-inch wood dowel, with three washers on the bottom to reduce friction between the top panel and the fiber reel. The reel was oriented horizontally so that a wheel and motor from an RC car could be attached to one of the side panels. The rubber wheel rotated the fiber reel and dispensed the fiber by making contact with the base, which provided enough friction to make it spin. As the robot moved forward, the fiber was concurrently dispensed.

The second skid-steer platform, Susan, was equipped with a Velodyne VLP-16 LIDAR and a second D435 depth camera facing upward to view more of the wall and ceiling to be searched. In

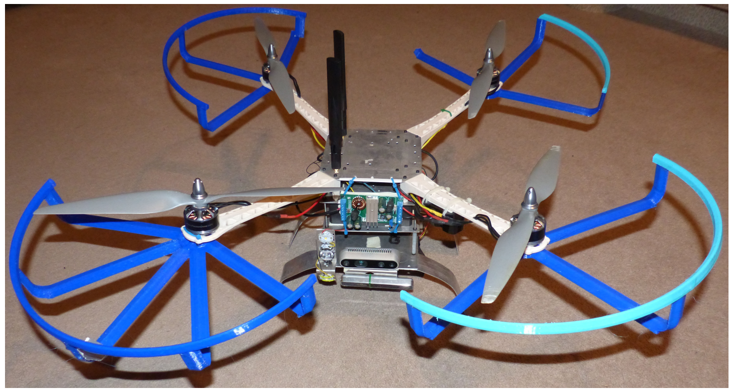


Figure 4. Aerial Vehicle.

addition, an SCD30 Sensirion Carbon Dioxide CO2 Sensor was added. An Arduino Uno interfaced with it and published the sensor readings to detect and locate gas artifacts.

2.2. Aerial

For the Urban Circuit, we took eight custom drones. As shown in Figure 4, each drone carried a payload of an Intel RealSense™ D435 depth camera, an Intel RealSense™ Tracking Camera T265, along with a Garmin LIDAR-Lite v3 altimeter. Each drone used a Gigabyte Brix GB-BRi5H-8250 (Intel i5-8250U) for processing that ran Ubuntu 18.04 and ROS Melodic. We had developed an image recognition solution that could use either a Coral USB Accelerator (4FPS) or the CPU (2FPS). Other CPU tasks (navigation, H264 compression, communication) used 1/3 of the available processing power. Due to lack of testing we did not enable image recognition on the Coral USB Accelerator or on the Gigabyte Brix and planned to have the operator identify images from the drones. Protecting the propellers in an indoor environment was a concern. Hence, a custom three-dimensional (3D) printed propeller guard was designed. In spite of efforts to prepare the drones in time for the Urban Circuit, they were not ready to fly reliably during the competition. Since the communication was working, we used one drone as a communications node. A plastic lid was attached to its landing gear and it was pushed into position by a ground vehicle.

3. The Software

Our solution used off the shelf ROS nodes, including drivers for hardware varying from motor controllers to LiDAR. The software we developed focused on light levels of automation, and communications interfaces. Figure 5 shows the interconnection of the various nodes within the ground robots.

3.1. Communications

Communications between different nodes or processes on a single platform were handled using standard ROS topics and services. Platform in this context means a single robot or the base station. The use of standard ROS topics allowed off the shelf use of a number of nodes and easier interfacing with the nodes the team created. The use of ROS topics also allowed simplified logging with rosbags.

Communications between platforms were handled with a custom user datagram protocol (UDP) based protocol. Messages on ROS topics were translated to the custom protocol and sent out as one or more UDP packets over the WiFi-based network. Once the messages arrived at their destination or destinations, the custom protocol was translated and sent out as a message to a ROS topic. The usage of the custom protocol allowed having a single ROS master on each platform and not having

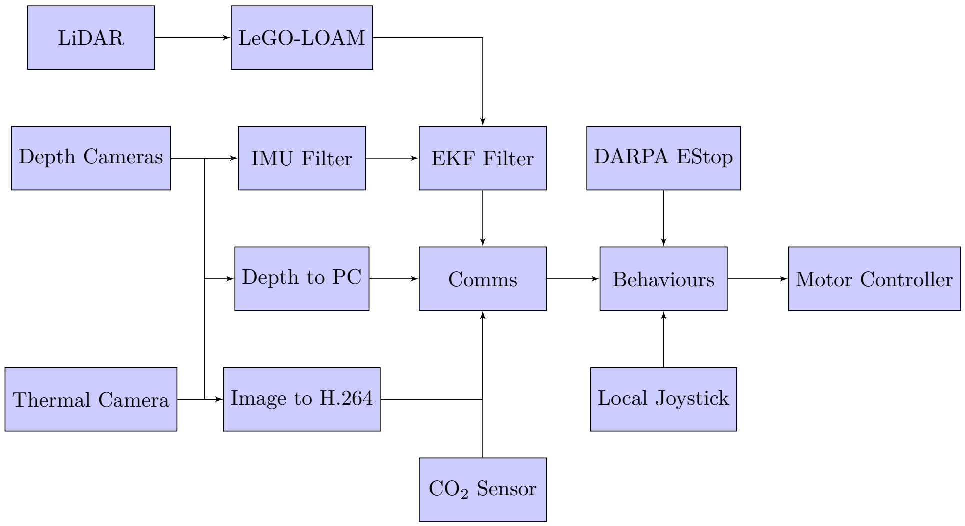


Figure 5. Graph of the interconnection of ROS nodes.

to use a Multimaster system. Because of this, we did not have to carefully control background bandwidth usage by ROS. The custom protocol also allowed smaller messages and easy real-time adjustment of bandwidth utilization.

In testing it was found that our network could reliably sustain 0.5 megabits per second if the total number of packets per second was kept under 50. Multiple robots receiving commands at 10 Hz and sending updates at 10 Hz exceeded that limit and reduced the available bandwidth for video and point clouds to less than 0.1 megabits per second. To reduce the number of packets, robot status and robot commands were reduced to a single packet. A single UDP packet carried commands to all of the robots and was sized to be below the MTU (maximum transmission unit) of the 802.11 and Ethernet based portions of the network. Similarly a below MTU sized packet returned status from the robots. Status from each robot was kept below 100 bytes so that each robot along the communications path could append its status while keeping the packet size below the MTU. Point clouds were downsampled, compressed, and split into smaller pieces so that each piece was small enough to not be fragmented. Image data from the cameras was large enough that the UDP packets containing image data were above the MTU and so the packets were fragmented when sent across the network. By minimizing the packets per second and the bits per second our network remained functional and allowed reliable teleoperation.

3.2. Localization and SLAM

For simulataneous localization and mapping (SLAM) a fork of LeGO-LOAM (Shan and Englot, 2018) was used that provided ROS parameter configuration implementation over an include file, this being LeGO-LOAM-BOR[1]. This node was configured for the 3D LiDAR sensors that were on three of our ground robots. This provided mapping and high precision odometry since wheel odometry was not available on two of our three primary exploration platforms. Sensor fusion was accomplished with the use of the ROS Extended Kalman Filter filter node robot_localization. This provides a 15-dimensional pose estimation by continuously estimating the current pose even in the case of a drop in sensor data (Moore and Stouch, 2014). This took inputs from the inertial measurement units (IMUs), from two of the depth cameras, and the odometry output of LeGO-LOAM-BOR. The IMUs were preprocessed by the ROS IMU Filter Madgwick node (Madgwick, 2010) to remove the

[1] https://github.com/facontidavide/LeGO-LOAM-BOR

gravity vector and provide data smoothing before fusion with the SLAM output. The final output was used as the estimated position of the robot to perform artifact position calculations and for operator representation.

3.3. Object Recognition

Images from the visual cameras on the large Ackermann platforms were processed with a custom model built with Luminoth (Luminoth, 2018). For other platforms the operator was expected to do the object recognition. The laptop GPU on the large Ackermann platforms was able to process images at 12FPS. The location of objects identified in the images was calculated using the depth information from the D435i cameras and localization information from the robot localization node. This information was passed back to the operator and could be submitted as an artifact report.

Detections of high levels of CO2 were sent to the operator. The cell phone artifact detection was not complete in our software at the Urban Circuit.

4. Teleoperation

4.1. Teleoperation vs Autonomy

In the continuum of teleoperation to full autonomy, our system ran towards the teleoperation end of the scale, as is common in Search and Rescue robotics (Delmerico et al., 2019). Rather than a common approach of two operators per vehicle, we had only a single operator with up to five vehicles deployed. To aid the operator mapping, localization, and object recognition features were available. These are described further in the user interface subsection. The use of teleoperation limited us to having a single vehicle actively moving at any one time.

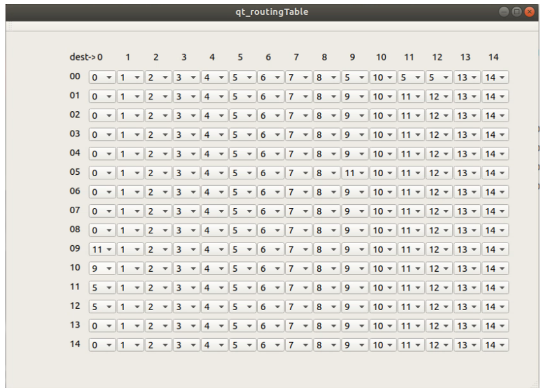
Our choice to be on the teleoperation end of the scale was largely driven by schedule constraints. Our first team meeting was roughly four months before the Urban Circuit. Although the robots had some autonomy for exploration, teleoperation was used due to a lack of testing and a few features that were not ready. In particular, the robots had not been tested near negative obstacles nor for various loss of communication behaviors.

4.2. Communications

Handling the difficult communications environment in the subterranean was accomplished by having multiple radio nodes along the transmission path. Rather than dropped repeaters or breadcrumbs, the communication nodes were the robots themselves. Each robot used a standard 802.11n WiFi transceiver. The first robot was driven in as far as radio communication would allow. The second was then driven past the first as far as radio communication would allow, and so on to extend the range of communication with the base station. In some cases, there were different branches or alternate paths used rather than a simple straight line. Routing was controlled by a qt interface. In Figure 6, you can see that the route from the base (row 0) to robot 9 (column 9) goes through robot 5 and then robot 11 before reaching robot 9 in this case. The operator knew the communication limits of a given robot node were being reached by monitoring the video feed, which would drop out. Once the video feed was lost the map could be used to move the robot back a short distance so that full communications and the video feed were restored. The operator could also monitor numerical packet status displays, but it was actually much easier and more intuitive using the video feed.

4.3. User Interface

In order to make operations smoother, a number of autonomy aids were provided to the user. LeGO-LOAM-BOR (Shan and Englot, 2018) was used with a Velodyne Lidar to provide vehicle positions and map data to the operator. An Rviz display, Figure 7, was used to keep track of the vehicle position and to provide a 3D map for navigation and identification of further areas to search.



qt_routingTable

dest->	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
00	0	1	2	3	4	5	6	7	8	5	10	5	5	13	14
01	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
02	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
03	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
04	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
05	0	1	2	3	4	5	6	7	8	11	10	11	12	13	14
06	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
07	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
08	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
09	11	1	2	3	4	5	6	7	8	9	10	11	12	13	14
10	9	1	2	3	4	5	6	7	8	9	10	11	12	13	14
11	5	1	2	3	4	5	6	7	8	9	10	11	12	13	14
12	5	1	2	3	4	5	6	7	8	9	10	11	12	13	14
13	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
14	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14

Figure 6. Routing table - sources are rows, destination are columns.

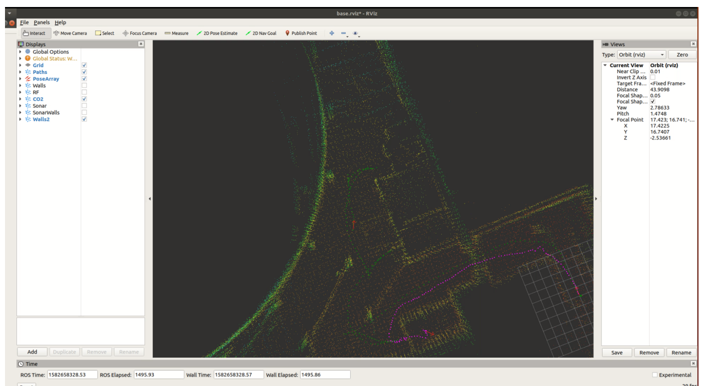


Figure 7. 3D maps and robot tracks in Rviz.

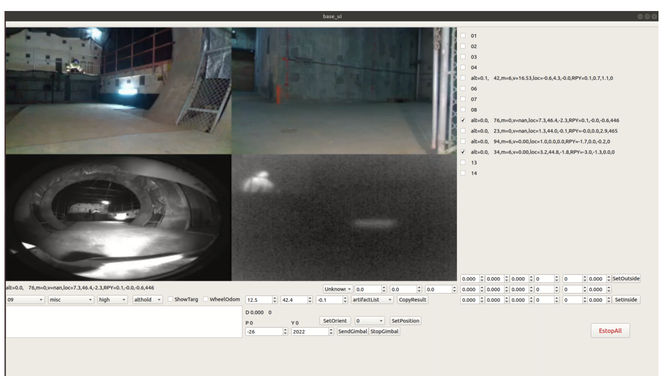


Figure 8. User and Camera Interface Window

The vehicle paths allowed the operator to know what areas had been searched and where each vehicle was located.

Automatic artifact recognition was provided to the operator. When one of the artifacts was automatically identified, a large red dot was shown on the camera view. Text data with the artifact coordinates was also provided to the operator to simplify artifact reporting to the scoring server.

Along with the automated aids, tools for selecting camera views and monitoring the status of each robot were provided as seen in Figure 8.

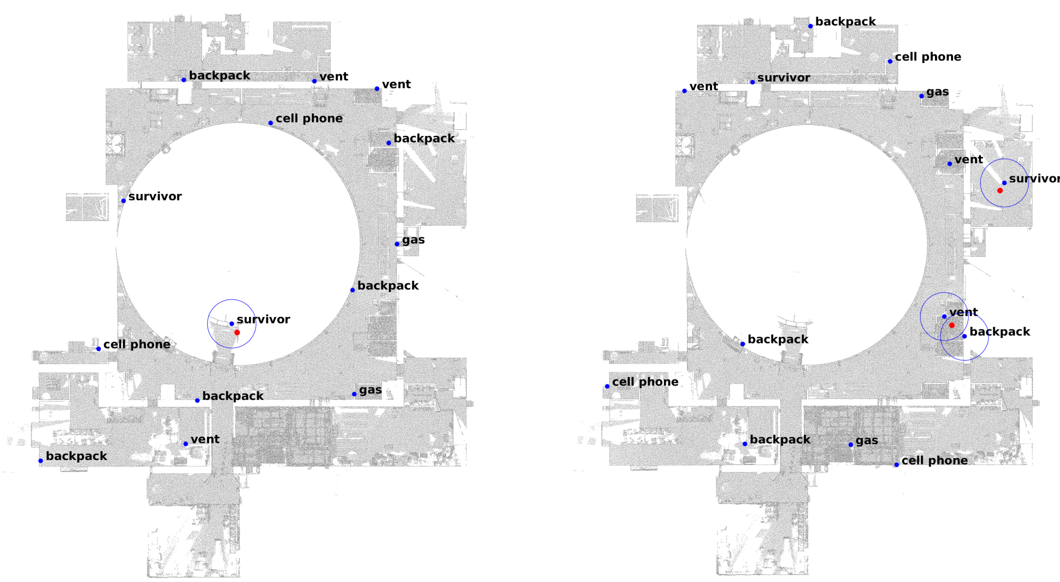
5. System Performance in Urban Circuit

In this section, we discuss the performance of the Coordinated Robotics team in the Urban Circuit of the DARPA SubT Challenge. Additionally, we share some insights based on our lessons learned from participating in this unique competition. We first discuss our performance related to mapping and localization of artifacts. Then we discuss the pros and cons of our teleoperation approach. Next, we discuss some of the difficulties associated with the terrain and communications, and our experience in trying to overcome these difficulties. Finally, we summarize our lessons learned from participating in the competition.

5.1. Mapping and Artifact Localization Performance

One of the biggest difficulties in the SubT Challenge is the requirement that artifacts must be reported within a 5-m error in order to be scored, without the benefit of global positioning systems due to the subterranean element of the challenge. To overcome this challenge, we used a SLAM algorithm based on LeGO-LOAM-BOR, and in addition to the human operator, we used Luminoth for artifact detection on the RGB camera. This combination proved sufficient to score points over the relatively small amount of the course that we were able to cover. The artifact localization performance for each run of the Alpha course can be seen in Figure 9. During run 1 we primarily explored the lower region of course where we were able to successfully locate a survivor artifact. During run 2 we primarily searched the upper and right regions of the course where we were able to successfully locate a survivor artifact, a backpack artifact, and a vent artifact.

An example of a successful artifact report can be seen in Figure 10. Figure 10a shows the RGB camera view of a survivor artifact that was located on a platform inside the main cylinder of the reactor while Figure 10c shows the same artifact captured by the thermal camera. Figure 10b shows the output of the image recognition software. Figure 10d shows the merged 3D point cloud produced by merging the maps created during both trials on the alpha course, along with markers for the



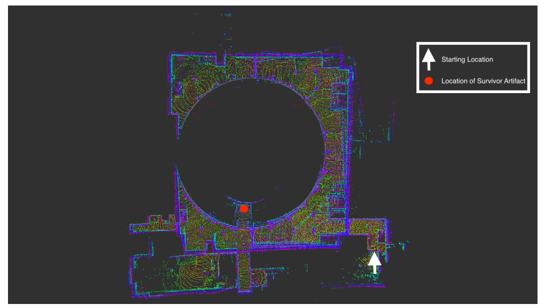
(a) Artifact localizations from run 1 on the Alpha course. **(b)** Artifact localizations from run 2 on the Alpha course.

Figure 9. A topdown ground-truth map of the first floor of the Alpha course with ground truth artifact locations from each run. For the artifacts that we successfully scored a red dot has been placed to demonstrate the location of our localization and a blue circle has been placed around the ground truth artifact location indicating the 5-m error limit.

(a) Camera image of a Survivor artifact located inside the reactor cylinder on the Alpha course.

(b) Survivor artifact correctly identified by the image recognition software.

(c) Another view of the survivor artifact through the thermal camera.



(d) The merged 3D point cloud from two trials on the alpha course.

Figure 10. The survivor artifact located on the alpha course imaged with both the forward facing RGB and thermal cameras and correctly identified by the image recognition system.

start location and located survivor artifacts. From Figure 10d it can be seen that our SLAM solution was beginning to become unstable, potentially resulting in failure had we been able to physically proceed further into the course. A similar result was observed when the SubT dataset was processed through a similar LOAM algorithm (Nubert et al., 2020).

5.2. Teleoperation Pros and Cons

With the team starting work only four months before the competition, our original goal was to score at least one point over the course of the entire competition. Thanks in large part to the teleoperation approach, we were able to exceed this goal to score at least one point in each of the four trials. By choosing to use a teleoperation approach, we were able to focus our efforts on integrating all of the sensing capabilities into our various platforms, thus greatly simplifying the software requirements of our system. This allowed us to quickly field a team of robots capable of accomplishing the tasks set forth in the challenge. Had we focused on adding full- or semiautonomy we would have likely been limited to fielding a single platform. In situations where rapid deployment is a priority, teleoperation could still be a viable solution although with some clear drawbacks.

The primary drawback to teleoperation is that within the constraints of the SubT Challenge, only one vehicle could be actively moving at a time. This greatly limited our search coverage area. For example, a team of four well-coordinated autonomous robots would have been able to cover approximately four times the area of our teleoperation system in the same amount of time. Another advantage of an autonomous solution would be optimal search paths. While a skilled human operator may be able to efficiently search a small area, as the mission expands, the cognitive load on the operator greatly increases. As can be seen in Figure 9, even though we only searched a single vertical level of the course, we had the potential to localize several artifacts had we been able to successfully detect them. This is partially explained by cognitive load on the operator, but a limited field of view of the D435i cameras accounts for some of the missed artifacts that were placed above our field of view. Finally, operator requirements could be reduced further by including advanced perception algorithms that detect potential hazards in addition to artifacts of interest. As we discuss in the next section, multiple robots became inoperable due to getting stuck in narrow corridors or rubble.

5.3. Terrain Difficulties

The Urban Circuit presented a variety of challenging terrains that would be difficult for a single robot to overcome. This included narrow corridors, rubble piles, step changes in elevation (up and down), and stairs. Coming into the competition we planned to use our variety of platforms to address the different terrains. For the narrow corridors, we planned to use the small skid-steer robots, Susan and Jeanine. The larger platforms were targeted at overcoming the rubble and small step changes in elevation, leaving our aerial platforms to cover the vertical passages and potentially stairs. Reflecting on the competition, this plan was reasonable and had the potential to work well. However, there were two notable problems that we encountered in practice. First, while the large Ackermann steer robots, Rick and Karen, had significant ground clearance and suspension systems, they were rear-wheel drive. When trying to drive over some of the rubble and some of the small curbs on the course we experienced traction problems that prevented those platforms from progressing further on the course. Additionally, these platforms were too large to enter some of the narrow corridors and doorways, thus limiting their search coverage to the larger chambers and passageways. The second difficulty we experienced was the stability of our aerial vehicles. We did not fly them during the competition due to a lack of confidence and because we did not want to take precious time away from other functioning ground vehicles.

5.4. Communication Difficulties

In addition to the terrain hindering mobility, it also greatly inhibited wireless communication capabilities. The walls of the nuclear reactor were made of thick reinforced concrete, virtually eliminating high bandwidth wireless communication through them. The course was designed with many orthogonal passages, limiting line-of-sight communications to only a few meters in many parts of the course. We deployed two approaches to address these challenges. First, given that we were using teleoperation and could only move one robot at a time, we used the robots themselves as repeater nodes. The strategy of driving one robot as deep into the course as possible before starting to lose reliable communication and then sending another robot deeper into the course in a daisy chain configuration enabled us to explore and search most of the area that we could physically reach with our vehicles. A second approach that we took was to deploy a robot (Jeanine) specifically to carry a fiber-optic dispenser. Our plan was to drive this robot as deep into the course as possible and position it at an intersection of the passages to act as a central communication repeater node. In practice this was beneficial, however, we did experience a failure of the dispensing mechanism. This caused the cable to bind and overturn the robot. While a redesigned dispenser would make this approach beneficial for this application, the combination of the rubble and right angle corridors would still limit the effective range of this approach.

5.5. Lessons Learned

We conclude this section by discussing the lessons learned from the competition.

- Run full scale practice sessions prior to the competition with the entire system. While it is impossible to fully prepare for the level of “DARPA-hard" that the competition poses, we wish we could have done more practice sessions with the entire system in a somewhat similar environment. Unfortunately, due to time and resource constraints we were limited to component level and scenario testing.

- Be prepared to make adjustments between runs. As mentioned above, there is no way to fully prepare for what DARPA will have in store for the competition, so it is important to learn from each trial and make adjustments accordingly.
- Having multiple sizes of robots was helpful. We utilized two sizes of robots each with their own strengths and weaknesses. The larger Ackermann steer robots were easy to control, could carry a large payload, and had high ground clearance. However, the competition courses contained narrow hallways and small rooms with narrow doorways thus limiting the search effectiveness of the larger vehicles in some areas of the course. The large vehicles were complimented by a pair of small skid-steer robots which were able to enter the narrow passageways, but they had limited payload capacity and ground clearance.
- Multimodal locomotion is imperative. While our fleet contained aerial vehicles, our approach was practically limited to the four ground vehicles and thus a single vertical level of the course. Even though these ground vehicles were able to search a significant part of the course, many of the artifacts in the areas that we did search were located above the field of view of our cameras. Had we deployed an aerial vehicle in the large rooms, we could have potentially located more of these artifacts.
- Autonomy not only increases the number of active robots on the course but also increases the range. By utilizing a teleoperation approach we were limited to a single active robot at a time, and our search coverage was limited by the range of our multihop communication network.
- In addition to autonomy, the communication range problem was addressed by some of the more successful team with drop-able communication nodes. While we did not have droppable communication nodes, we instead positioned robots (including grounded aerial vehicles) to extend the range of our network.

6. Conclusions

A teleoperation strategy for mobile robotic exploration, mapping, and search of a complex urban underground environment was proposed and described. The presented solution required the integration of several sensing modalities and algorithms for object detection as well as localization and mapping in order to overcome the difficulties associated with this application domain. The results of the DARPA SubT Challenge indicate that a teleoperation strategy, while possessing several critical limitations, can provide a feasible alternative to fully autonomous solutions. The team successfully navigated portions of the course, detected artifacts, and returned their locations with sufficient accuracy to score points. The main limitations observed with this approach were related to difficulties in maintaining a reliable communication network to the base station and the inability to operate multiple platforms simultaneously. These two challenges resulted in search coverage that was less than achieved by other autonomous strategies.

In future rounds of this competition, we plan to add semiautonomous capabilities to our robots. This will require improvements to the robustness of our communication network, object detection algorithms, and autonomous navigation algorithms. Additionally, we are currently working on platform related changes based on advantages that we observed from other teams at the Urban Circuit including breadcrumb communication nodes that can be deployed by the ground vehicles, a marsupial system for carrying aerial vehicles into the environment, and the addition of tracked vehicles for their ability to traverse more harsh terrain, including stairs. We envision operating multiple robots simultaneously, with each robot possessing the ability to detect when human intervention is required. This, coupled with the ability to return to the last known communication point, will enable greatly expanded search coverage.

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ORCID

Jason T. Isaacs https://orcid.org/0000-0002-7719-3627
Kevin Knoedler https://orcid.org/0000-0002-1684-9047
Andrew Herdering https://orcid.org/0000-0002-1718-5166
Mishell Beylik https://orcid.org/0000-0003-2308-1336
Hugo Quintero https://orcid.org/0000-0002-0439-9376

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