3D Modeling of Subterranean Environments by Robotic Survey

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Abstract. This paper presents a method for autonomously collecting survey-quality data from underground spaces for the purposes of 3D modeling. This overview includes a systems-level description of the robotic tools, data acquisition process and data processing techniques that enable accurate 3D modeling of subterranean interiors. A performance evaluation and accuracy analysis between the capabilities of this robotic system and human surveying is also provided.

1 Introduction

Subterranean applications offer exceptional opportunities for robots. Hazardous, remote and space constrained, underground spaces such as mines, tunnels, caves and sewers are difficult environments for people to reach and work; yet, information acquired from the subterranean has immense civil and commercial value [1]. Compact, sensory-tailored robotic systems provide practical solutions to subterranean information-gathering efforts by reaching spaces and collecting data on a scale that was once not feasible.

One of the significant challenges facing robotic information-gathering in underground applications is the availability of accurate position and pose information in the absence of GPS. This paper explores the use of robotic surveying as a method for acquiring high-fidelity position data such that a robot's sensor footprint can be accurately registered to a global coordinate frame. In this context, LIDAR scans, photographs, thermal images, gas concentrations, moisture levels and countless other sensing modalities can be spatially co-registered to provide an unrivaled virtual view of subterranean voids. The underlying processes for accruing and fusing subterranean information into a consistent and accurate model, however, are labor-intensive tasks; hence this work seeks to construct a fully automated system for data acquisition, model construction and reporting.

This paper presents a systems-level overview of the subterranean modeling process starting from data collection and concluding with model presentation. The structure of this paper is as follows: Section 2 describes a robotic survey team that cooperatively gathers the necessary sensor data from a subterranean space. Section 3 details the techniques employed to reconstruct the void's interior from logged robot data. Section 4 showcases a collection of results obtained by this procedure and Section 5 concludes with a forecast of research and enterprise for this technology.

2 Data Collection and Robotic Survey

Robotic equipment is revolutionizing geological data collection in work environments such mines and quarries by reducing the time, managing the repetitive nature and minimizing the error associated with measuring natural surfaces over vast ranges. Laser profiling systems, for example, integrate video with LIDAR images, which record of hundreds of thousands of individual range measurements, to create high-resolution surface models for detailed burden analysis in quarries and surface mines [2]. Robotic total stations and GPS are enabling rapid acquisition of highly accurate positioning data to spatially geo-reference natural and man-made geologic features [3]. Together, these and other related surface-scanning technologies are saturating the world with geospatial data on and over the Earth's surface.

Subterranean environments, characterized by confined spaces, harsh conditions, limited accessibility and the absence of GPS, prohibit direct utilization of modern surface mapping methods [1]. To address these problems, the field of subterranean robotics has produced a number of platforms, sensors and algorithms to reach, sense and model a variety of underground spaces [4,5,**Error! Reference source not found.**].

Figure 1: Combined survey instrument and mobile robot.

The most recent technique to emerge from subterranean robot development is a method for robotic surveying, which provides a direct mechanism to maintain a robot's global position while accruing underground data. Similar to a method employed to accurately position robotic mining machinery [7], robotic surveying utilizes a total station (e.g. an actuated and highly accurate range-measuring laser) to track the position of a mobile platform equipped with a special reflective prism (Fig. 1). As the robot moves and scans a subterranean space, the survey instrument monitors the robot's position by following the robot's onboard prism.

Pose information (i.e. the orientation of the robot) may also be obtained by either outfitting the robot with multiple prisms or mounting one prism to an actuated platform located on the robot. The computed differential between relative prism locations on the robot provides an estimate of body orientation that can align each of the robot's sensors to a particular vantage. The accuracy of this pose estimate can be further enhanced through the incorporation of inertial sensing.

Data collection is a completely automated procedure for the reasons previously described: efficiency, repeatability and accuracy. The robot seen in Fig. 1, know as Cave Crawler, is designed to use an assortment of sensors that are well-suited for subterranean model construction such as 3D LIDAR, low-light video, a high-resolution still camera, radar, a thermal camera and inertial. To obtain a sensor coverage capable of reconstructing subterranean surfaces to within centimeters of accuracy, the robot moves, stops and thoroughly scans the subterranean interior in continuous repetition. During each scan, the robot moves its survey prism to four locations and queries the survey instrument to measure each prism position. After obtaining these measurements, the robot resets the prism position to a specified start position and moves to the next scan location. This cyclic operation transpires in clockwork fashion until the robot has completed its survey, is halted by error or is stopped by human intervention.

Navigation and scan position is robot controlled, but human operators can dynamically adjust trajectory characteristics to suit the environment. The navigation scheme employed on Cave Crawler is a behavior-based system where simple steering routines are managed by higher-order control logic. Akin to known mine navigation methods of [8,9], low-level steering behaviors are reactive; however, Cave Crawler extends these prior 2D schemes to 3D to take advantage of its 3D LIDAR[1]. At moderate speeds (human walking pace) this simple reactive 3D navigation scheme has shown to be empirically robust.

Higher-order navigation is based upon a topological command structure [4]. The robot is provided with pairings of <distance, action> commands prior to the start of the survey. A typical command list, for example, would have the robot drive straight for 90 meters, turn left, continue for another 30 meters, turn right, and etc. Scanning locations are therefore defined as waypoints (i.e. specific increments) along this path. In addition, both the topological commands and waypoint increments can be dynamically altered during the robot's traverse.

At present, human interaction is required to place and initialize the survey instrument at the start of each operation and to continue the

[1] A detailed description of this reactive 3D navigation scheme is beyond the scope of this paper, but shall be forthcoming in future publications.

operation once the robot and survey instrument lose line-of-sight contact. For this reason, this system is restricted to surveying areas where humans have access to manually place the survey instrument. Section 5 discusses future plans to remove this restriction by robotically mobilizing the survey instrument.

3 Automated Model Construction

Just as data collection requires automation for reasons of efficiency and accuracy, data processing is tedious and error-prone without the proper autonomous tools to manage the volumes of data logged from robot sensors. Model synthesis requires that all data be synchronized, fused and spatially registered into a global coordinate system. As such, data synchronization begins online while the robot is collecting data. The Cave Crawler system is constructed with a modular software architecture that specifically monitors and regulates data flow [12]. Every sensor and input device is time stamped and logged. Handling data in this manner allows for complete offline playback of the data and provides a timeline to organize streaming data into discrete model-building blocks (see Fig. 2).

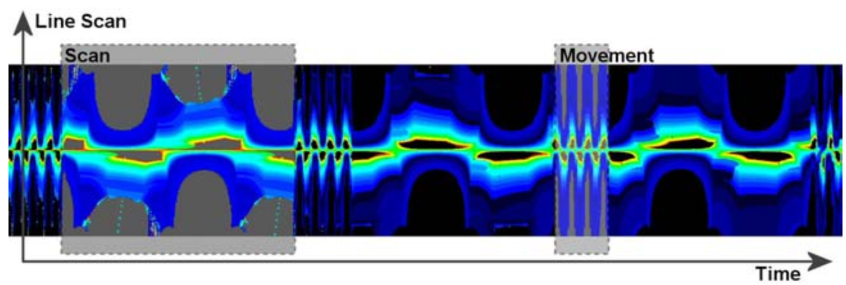

Figure 2: A 3D LIDAR data stream. Each column of pixels is a line scan of range measurements. Each row follows a particular measurement over time. 3D data is obtained by rotating the line scanner at an angular rate. In this figure, two different rates are depicted: one for scanning and one for navigation. The large dashed box is a block of data representing a single, fixed-position scan while the small box is a block of data showing what the robot uses for navigation. The data highlighted by the large block corresponds to the images shown in Fig 3.

Once data is blocked into time segments, these blocks are aligned and registered into a model. LIDAR data streams and survey measurements, for example, are blocked into point clouds and robot position/pose data, respectively. Point clouds are filtered for outliers and globally registered using the surveyed position and pose estimates as the starting point for multi-view surface matching [10] and global ICP [11] algorithms. Fig, 4 shows a 2D map generated from 172 scans of varying views that were autonomously registered from these algorithms.

Following scan registration, updated position and pose information (obtained through the registration process) corrects orientation for all robot sensors. This step allows data from each sensor to be globally registered and thereby visually represented as texture on a 3D model. Spatial visualization of non-geometric data greatly enhances the aesthetic appeal and contextual understanding of 3D models. One example of this texture mapping capability is shown in Fig. 3 where high-resolution fisheye photographs are un-warped and applied to the surface model. This procedure takes a projected 2D image plane and, though knowledge of camera and lens parameters (obtained via calibration), maps every image pixel to ray on a unit hemisphere. Using this transformation and the relative LIDAR and camera poses, each point in the range image is colored with information from the fisheye image.

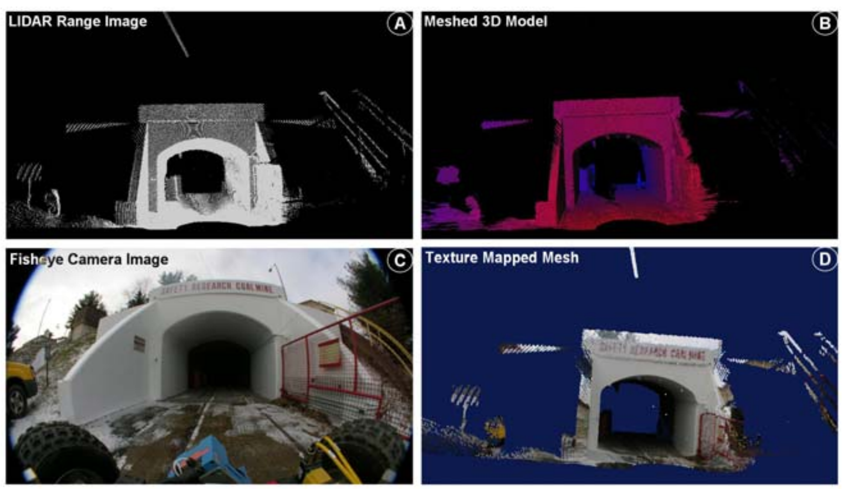

Figure 3: Production of a texture-mapped mesh. (A) Raw LIDAR data is visualized as a point cloud whereas in Fig. 2, it was shown as a data stream. (B) A surface (or mesh) is applied to the point cloud. (C) A fisheye image of the scene is taken during capture of the LIDAR image. Note: the LIDAR sensor is visible at the bottom of the photograph. (D) Image pixels paint the mesh to produce the final textured-mapped model.

4 Results

The described system has undergone extensive utilization in a variety of underground domains. The results show in Fig. 2,3,4 were acquired from a research coal mine located outside of Pittsburgh, PA.

Similar results have also been logged in limestone mines, concrete passageways, hard rock tunnels and indoor settings.

The earlier claims that robotic surveying provide efficiency, repeatability and accuracy for subterranean data collection are supported by the results shown in Table 1 and Fig. 5. Table 1 shows a comparison among human, mixed human and robot and robot-only surveying operations in terms of operational performance. Fig. 5 shows a comparison between a human-surveyed mine map and one generated by taking slices from a robot-surveyed mine model.

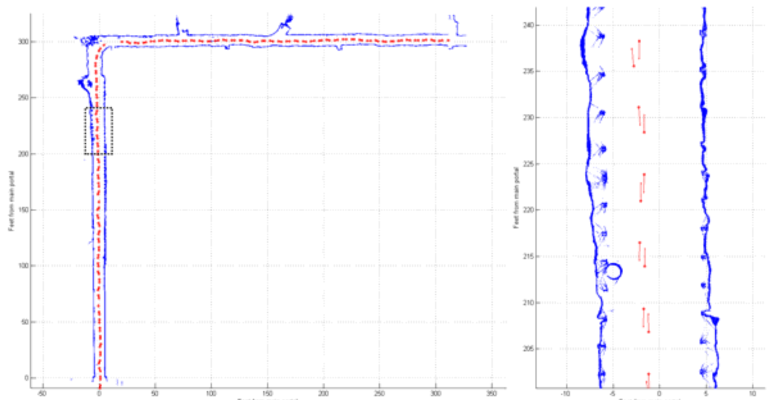

Figure 4: Scan Coverage. (Left) This map is actually a thin slice of data extracted from a robotically generated model. This model contains 172 individual LIDAR scans that were fused from 86 robot stations covering 183 meters of mine corridor. (Right) A magnified view of this map showing a 12m section of corridor. The arrows in the center of the map show the position and heading of each LIDAR scan.

Table 1 summarizes performance results recorded from actual field data[2] in three modes of operation: **H** for human-only, **HR** for mixed human-robot and **R** for robot-only. All three data sets utilized the same equipment (i.e. robot and surveying instrument), followed the same procedure of moving and scanning as described in Section 2 and occurred in different yet comparable subterranean environments. Human-only data required a team of two people to manually operate the survey instrument and puppeteer the robot. Human-robot data required one person to operate the survey instrument while the robot autonomously navigated, scanned and signaled the human to take survey measurements. Robot-only required a human to monitor the surveying process, but the operation was conducted without direct human interaction.

[2] Field data means the operation occurred in subterranean settings. No laboratory results are included in these results.

Table 1 is composed of the following information: The sample size for each of these results is denoted by the **Size** column and is in units of robot stations (i.e. the number of scan-transition cycles). To accurately portray performance characteristics, stations where errors occurred were removed from statistical computations. In this work, errors are considered to be stations where one or more of the survey readings were corrupted or the cycle time was larger than two standard deviations from the sample mean. Average error is reported in the **Err/Size** column. The error-free averages (fist number) and standard deviation (highlighted second number) of the scan and transition times (in seconds) are reported in columns **S-Time** and **T-Time**, respectively. The estimated period (in seconds) for scan-transition cycles are show in the **Period** column.

Table 1. Survey Performance Comparison

Mode	Size	Err/Size	S-Time (s)	T-Time (s)	Period
H	116	0.086	73.08±15.14	54.48±18.17	127.56
HR	160	0.044	75.71±0.59	23.26±0.05	98.97
R	106	0.035	76.86±7.79	23.27±0.05	100.13

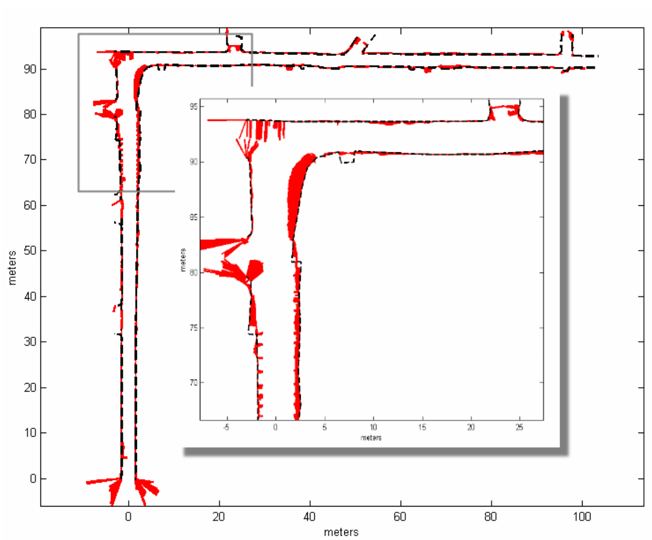

Figure 5: Map Comparisons. The original mine map is represented by the dashed line. Differences between the prior and robot-generated maps are signified by the colored area surrounding the dashed line. The robot-generated map remains consistent to the "idealized" mine map; however, locations where mine interior has changed are distinguishable.

The results in Table 1 show clear performance improvements as robot autonomy is incorporated into the surveying process. The error rates are a factor of 2 higher in human surveying verses robot autonomy, with full autonomy showing a slightly lower error rate than mixed human-robot. The mean survey time is consistent over all modes; however, the reported deviation in human operation time is double the repeatability of robot-only. Transition time shows the greatest difference in performance with human surveying appearing two times slower than automation. This result is a consequence of the costly preparation time required to manually move the robot verses the small overhead involved in allowing the robot to move itself. The error margin in these between-scan transition times is 1/20th of second for the robot and 18 seconds for the human. Interestingly, this transition-time statistic is repeated for **HR** and **R** modes because the robot is fully automated during this part of the process in both modes. Altogether, these numbers show the automated system being 21.5% faster than the human-only system and 28% more productive.

In prior evaluations, the reported accuracy of this process has been shown to be within 8cm of surface measurements acquired by alternative profiling technologies such as human survey and stationary laser profiling systems. Fig. 5, for example, shows the difference between a decades-old human-surveyed mine map and one generated through robotic survey over a traverse of 183 meters. In areas where concrete walls exist, which define a flat and easily comparable surface, the prior map and robot survey are within 7.24cm of each other. Natural surfaces, such as the rock wall, are within 15cm of each other; however, the human survey tends to "idealize" walls whereas as robotic survey captures the true interior surface. Topologically, intersections align exactly to locations specified on the prior map. The notable differences are caused by alterations in the environment. As shown in magnified portion of Fig. 5, equipment and structural modifications dramatically alter the subterranean surface, which suggest yet another interesting application for this technology: the ability to produce temporal subterranean maps that monitor change over time.

Visualization and analysis tools are show in Fig. 6. The left portion of Fig. 6 shows a multi-view registration utility that colors individual point clouds inside of a 3D model. This colored model assists in quickly assessing potential problems that may have occurred during the automated registration process. The right portion of Fig. 6 shows a tool for extracting area and volumetric measurements from model information. Such tools are invaluable for data interaction and can also be automated to produce sectional views and record measurements over long stretches of model.

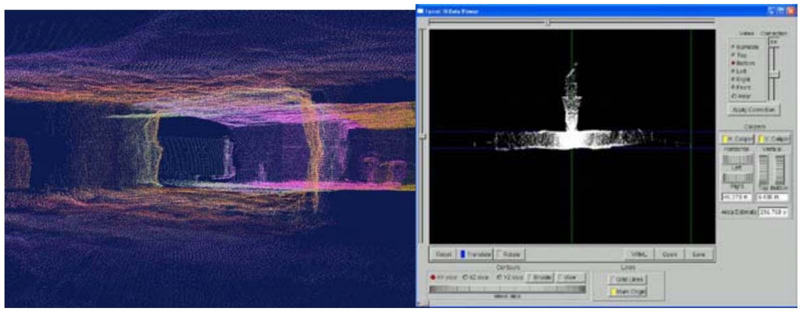

Figure 6: 3D Data Manipulation. (Left) A limestone mine model is visualized by coloring each individual scan with a random color. This model can be flown-through, meshed or cut into cross sections as needed. (Right) Analytical tools provide measurements from subterranean models in the form of cross sections, area and volume calculations.

5 Future Work

As mentioned in Section 2, human access is limited in many underground applications; therefore, manual placement of the survey instrument by a human is not always possible. Currently, methods for integrating the survey instrument onto a second mobile robot are under investigation such that human accessibility is not an issue.

In addition to a variety of technical improvements for robot autonomy, human interfaces and model construction, one of the most significant looming challenges is data cataloging and management. As demonstrated, subterranean robots are capable of archiving massive amounts of information, which over time will become increasing difficult to organize. Powerful and innovative solutions are necessary to store, search, reconstruct and visualize these libraries of underground data for future users.

Robotic surveying is also shaping new opportunities in enterprise. The economic potential of this work is already having an impact as geotechnical and engineering firms can now gain access to information that was once expensive or impossible to obtain. As a side note, much of the data presented in this paper was acquired with the assistance of one such company, Workhorse Technologies. Similar corporate and university partnerships will be essential for transitioning this technology from experimental settings to the industrial workplace.

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