LiDAR-based Simultaneous Localization and Mapping in an underground mine in Złoty Stok, Poland

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Abstract. The mining sector is one of the most promising areas for implementing advanced autonomous robots. The benefits of increased safety, robot actions’ repeatability, and reducing human presence in hazardous locations are especially important in underground mines. One of the core functionalities of such a device is the robot’s ability to localize and navigate itself in the working environment. To achieve this, simultaneous localization and mapping (SLAM) techniques are used. In selected cases, they also allow the acquisition of dense spatial data in the form of 3D point clouds, which can be utilized for various 3D modeling and spatial analysis purposes. In this work, a mobile robot, equipped only with a compact laser scanner, is used to acquire spatial data in the adit of a closed mine in Złoty Stok, Poland. This data is further processed with selected SLAM algorithms to create a homogeneous 3D point cloud. Results are visualized and compared to a model obtained with a survey-grade laser scanner. Accuracy evaluation shows that employing SLAM algorithms to process data collected by a mobile robot can produce a reasonably accurate 3D geometrical model of an underground tunnel, even without incorporating any additional sensors.

1. Introduction

Automation and robotization of various industrial processes are inevitable steps of the mankind technological advancement [1]. Since they provide an ability to reduce or even totally exclude the direct involvement and physical presence of humans in the place of work, one of their most important advantages is the increased safety of employers. This is a crucial issue especially in sectors such as mining, where in many cases, there is a substantial risk of a serious or even fatal accident. Furthermore, if such an accident happens, an underground mine is arguably one of the most challenging environments for carrying out a rescue mission. Using mobile robots in this circumstance would not only help the rescue team safely reach victims, but also employ more sophisticated techniques of localizing them, utilizing sensors mounted on a robot [2, 3].

Deploying robotic devices in a mine can also facilitate the employment of novel techniques of mining machinery monitoring [4]. This is a rapidly growing field, in which one could find examples of using mobile robots for the acquisition of acoustic signals [5], infrared thermography imagery [6] or LiDAR-based point clouds [7] to evaluate the condition of various belt conveyor parts. Unmanned robots and mobile sensors have been also used for monitoring environmental conditions in an underground mine [8, 9].

One of the basic requirements of allowing an inspection robot to safely operate in a mine is achieving its spatial awareness. It should be a core capability of a robot to localize itself, map...
and analyze its surroundings, in turn to be able to navigate to certain places for accomplishing the subsequent goals of a defined mission. Solving those issues is a serious challenge in the environment of an underground mine, where uneven illumination, dust, humidity, high temperature and rough terrain are often present. However, such a solution could simultaneously produce another valuable outcome - 3D geometrical model of the environment, which could be used for various other analytical purposes. Currently, such models are acquired with data collected with survey-grade laser scanners used by mine surveyors. While they can provide superior accuracy and resolution of the resulting point cloud, they are expensive and their usage involves the surveyors’ physical presence in the place being measured. In this work, a solution to those problems utilizing Simultaneous Localization and Mapping (SLAM) algorithm to process LiDAR data acquired with a much cheaper, industrial-grade instrument will be presented.

The paper is organized as follows. Section 2 describes the robot and sensors used in the experiment carried out in a closed mine in Złoty Stok, Poland. It also outlines the methodology of processing data from both LiDAR scanners, comparing the results and evaluating the accuracy of SLAM-derived model. Section 3 presents the results of the experiment, including the visualization of the raw data, final geometrical models and outcomes of point clouds’ comparison. The last section contains conclusions from this research and indicates plans for future work.

2. Methodology

In this study, a SLAM approach has been tested for creating 3D representations of mine tunnel geometry. A SLAM problem is defined by an observer located in an unknown environment where he must simultaneously determine and update his position on a map of the environment and construct and update the map itself. Many researchers utilized various sensors to solve this issue. The most common types of sensors used for mobile robot localization are cameras [10, 11] (visual SLAM), LiDARs [12, 13, 14], ultra-wideband localization [15, 16] and inertial systems [17]. Regarding the dimensionality of the map and the observer’s pose space, a SLAM problem can be considered in 2D or 3D space, leading to a 4 degrees of freedom (DoF) or a 6 DoF problem. A SLAM can be robustly and efficiently performed, taking into account the robot’s movement over a perfectly flat ground only and constructing a two-dimensional map [18]. The latter version of the problem is much more problematic, especially in demanding conditions.

Various SLAM versions have been tested in mining environments. In [19], 2D Hector-SLAM has been applied to create a map of the underground tunnel. The possibility of applying various versions of 3D LiDAR SLAM for the purpose of enabling autonomous vehicle operation in the tunnels of an underground mine was examined in [20]. Another study concerned developing a methodology of updating a high-resolution open-pit mine model with a cost-effective and fast 3D SLAM solution [21]. In the work of [22] extensive tests of a SLAM system for autonomous mining vehicles were carried out. However, the study concerns mostly the ability to create a simple 2D map of the mine and localize the vehicle in it. The research of [23] concerned a close-source handheld SLAM system, a GeoSLAM ZebRevo. The instrument was tested in underground conditions and results obtained from handheld scanning and from measurements, when the scanner was mounted on a vehicle, were compared. Authors underline the fact that proper usage in the mining environment should be restricted to short scanning periods and unstructured underground conditions still pose a challenge for SLAM algorithms, indicating the need of further research in this area. The same sensor was utilized in the study of [24] to not only create 3D point cloud of an underground adit, but also construct a local geological model through identification of fault zones.

In this work, an unmanned ground vehicle (UGV), equipped with a Velodyne VLP-16 LiDAR, was used to carry out SLAM tests. The unit is shown in the Figure 1. The measurements were performed in the adit of a closed underground gold mine in Złoty Stok, Poland. The adit is currently used as a geotouristic place, so the ground flatness and lightning conditions are not
as extreme as in an operating underground mine. However, they differ substantially from more structured environments, such as buildings.

The data from the LiDAR was acquired using a laptop running Ubuntu 18.04 LTS and Robot Operating System (ROS, [25]), placed on the robot. A SLAM algorithm, High-Density LiDAR SLAM (HDL-SLAM) [26] was chosen for processing this data. It provides vast possibilities of customization (e.g. different methods for scan matching, changeable parameters, ground detection and voxelization) and is compatible with the post-processing interactive tool [27], allowing to verify validity of scan matching, manually edit erroneous connections and refine the pose graph with robust estimation. The above-mentioned software is compatible with ROS and is shared online under a 2-Clause BSD license (HDL-SLAM) and GNU General Public License v3.0 (post-processing tool).

After carrying out measurements with the mobile robot, a survey-grade laser scanner was used to obtain the ground truth 3D model. The instrument employed for the survey was Riegl Vz-400i (shown in Figure 2), providing point cloud accuracy of approximately 5 mm. The instrument was additionally equipped with a Nikon D810 digital camera, which allowed to generate colored point cloud visualizations. The scans were cleaned, registered and transformed into a homogeneous local coordinate system using cloud-to-cloud technique in the Vercator cloud software. The SLAM point cloud was matched to the reference model using the iterative closest point (ICP) algorithm and the unsigned distances from points to the reference model were calculated. To minimize the influence of gaps that could appear in the reference measurements and not in the SLAM-based model, thus distorting its accuracy evaluation, the distances were estimated using local surface modeling of the reference point cloud using the quadric local model. Histogram of those distances was calculated and analyzed, as well as basic statistics. Finally, the spatial distribution of the estimated error values was examined.
3. Results and discussion
The drive through the 130-meter long tunnel took approximately 5 minutes. The robot collected 2978 scans, which were saved to a .rosbag file. The LiDAR’s field of view was reduced to 270° due to the hardware mounted on the robot, obstructing the view behind the sensor. The UGV, as shown in Figure 3, was additionally equipped with a compact light source to aid the operator’s ability to control the machine in the dark parts of the corridor.

![Figure 3. Mobile robot equipped with a Velodyne VLP-16 and a laptop for data collection](image)

In the next part of the experiment, Riegl LiDAR was used to measure the tunnel, which was scanned from 8 positions, totalling 120 949 585 points. The clouds have been manually cleaned using Cloud Compare software. Scans were then registered in the Vercator cloud software, using manual prealignment and cloud-to-cloud method. Average root mean square error (RMSE) of the point-to-point error for each pair of clouds has been calculated during the alignment. Since the expected accuracy of the SLAM point cloud is definitely greater than a centimeter, the resulting error of 1.6 mm is satisfactory and justifies using this point cloud as a reference model for the accuracy evaluation of SLAM. Finally, the reference point cloud has been subsampled to the resolution of 5 mm to homogenize its spatial resolution. Render of a colored point cloud can be seen in Figure 4.

![Figure 4. Render of a colored reference point cloud acquired with a survey-grade laser scanner](image)
Scans collected with a mobile robot and stored in a .rosbag file were processed in an offline mode to ensure repeatability and the possibility to test different parameter values and modes of HDL-SLAM. They were, however, replayed as a stream of LiDAR scan data and processed in real time. As for the SLAM settings, the generalized iterative closest point (GICP) algorithm was used as a basis for scan matching and ground plane detection was enabled to aid the correct orientation of subsequent scans with respect to the Z-axis. The obtained graph was optimized with Levenberg–Marquardt algorithm. After the first step of real-time processing, the resulting pose graph was refined and optimized in the post-processing mode, enhancing the graph edges using Huber robust kernel to improve scan registration. The resulting point cloud was cleaned in the same manner as the reference data set by removing distinctive outliers. The final point cloud is shown in Figure 5. The resulting point cloud contained 357 468 points.

Registration of the SLAM-derived point cloud to the reference point cloud was carried out in Cloud Compare software. With the random sampling limit of 100 000 points, the resulting RMSE amounted to 14 cm. Visualizations of both point clouds transformed to the consistent local coordinate system can be seen in Figure 6 (the tunnel interior) and Figure 7 (top view). Nevertheless, the examination of the results shows that the SLAM-derived tunnel geometry is mostly locally consistent with the reference data. The errors are mostly due to the drift of the sensor position estimation, since no loop closure was present in the acquired data.

![Figure 5. Render of a point cloud produced by the HDL-SLAM algorithm](image1)

![Figure 6. The tunnel interior. SLAM point cloud in blue, reference cloud in red](image2)

![Figure 7. Top view of both point clouds. SLAM point cloud in blue, reference cloud in red](image3)
Distances between SLAM point cloud and the ground truth data were calculated. The surface of the reference model was approximated with a local quadric model fitted in the closest neighborhood of each point. The outcome values were used to color the SLAM point cloud according to the estimated errors. The top view of such visualization is depicted in Figure 8. A histogram of distance values was plotted (Figure 9) and the basic summary statistics were calculated (Table 1). Estimated point position errors follow a half-normal distribution, since the unsigned distances were calculated.

![Figure 8. Accuracy evaluation - distances between reference and SLAM point cloud](image)

| Statistic         | Value [cm] |
|-------------------|------------|
| Median            | 8.3        |
| Mean              | 11.8       |
| 95th percentile   | 34.0       |

![Figure 9. Accuracy evaluation - histogram of distances between reference and SLAM point cloud](image)
The obtained results prove that LiDAR SLAM can be successfully used for generating 3D models of the highly unstructured corridors of an underground mine. Uneven ground and irregular geometry of the tunnel, especially the walls and the roof, pose a challenge for correctly matching subsequent, sparse LiDAR scans. However, proper parameter tuning of HDL-SLAM, manual verification and refinement of the pose graph in the post-processing step allowed to obtain reliable results. Gross errors of the final point cloud, caused by a quickly growing cumulative error of the pose or failing to register following scans, showed in [20] in case of applying selected SLAM algorithms in the mining environment, are not present. Accuracy and point cloud density of the tested simple solution is clearly worse than the point cloud data collected with a survey-grade scanner, but the resulting model is still locally consistent and could be used for GIS or robot navigation purposes. Despite this, there are lessons to be learned for the future from the research presented, which could potentially improve the SLAM performance in future applications. Firstly, the main reason of large error values is the drift of robot positioning, gradually skewing its trajectory. To cope with this problem, measurements have to be planned to ensure (optimally several) loop closures. Secondly, as seen in Figures 5 and 6, the highest SLAM point cloud density is concentrated on the lower and middle parts of the corridor walls. This should be attributed to the horizontal placement of LiDAR sensor in the same plane as the robot movement. Because of that, more sparse data is collected about objects located higher up and gaps can appear in the resulting model. A different placement of the sensors with respect to the robot base could be tested to address this issue, e.g. by tilting the LiDAR relative to the robot’s main motion plane by a constant angle or by continuously rotating the sensor around its front-facing axis.

4. Conclusions

The conducted experiment shows the possibility of employing SLAM techniques to model the highly irregular geometry of an underground mine tunnel. Even though the relatively simple solution, utilizing only a single LiDAR sensor was tested, the accuracy evaluation of the resulting point cloud indicates that such a model could be used for various purposes, e.g. digital twin creation, flow modeling, volumetric calculations or robot navigation in a mine. In harsh conditions of an underground mine, factors such as dust, rugged terrain or darkness can render SLAM solutions heavily relying on camera vision or IMU readings nonfunctional. For this reason, the ability to rely solely on LiDAR SLAM is very valuable.

Conclusions from this research will allow to enhance the configuration of the demonstrated UGV 3D scanning platform for future applications. Potential works include automation of data acquisition with autonomous exploration of the unknown environment of an underground mine and improving SLAM accuracy with enhanced LiDAR mounting on the robot. Another prospective field of research is testing the proposed solution enhanced with data fusion techniques. Integrated supplementary sensors could include another LiDAR, cameras, IMU or wheel encoders.

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