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APPLICATION OF DATA ANALYTICS USING ARTIFICIAL INTELLIGENCE IN THE FIELD OF UNDERGROUND MINES USING DATA DRIVEN PROSPECTS

***Amar Nath Singh and Prasanna Kumar Sahoo**

Department of Computer Science & Engineering, Gandhi Engineering College, Bhubaneswar, Odisha, India

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ABSTRACT

The field of machine learning and artificial intelligence (ML/AI) is rapidly evolving today and slowly beginning to reshape the mining sector. With the mining machinery becoming larger and equipment more sophisticated, the sector can gain immensely from these advanced technologies in terms of operational efficiency and ramping down costs. ML/AI is a field of computer study that deals with the creation of intelligent machines that work and reacts like humans. It covers a wide spectrum from speech recognition and visual perception up to language translations and decision-making, which normally require human intelligence. ML algorithms and AI is considered the next step for digital mine transformation. AI can be successfully leveraged at different stages of mining to identify and unlock potential use cases. From the prospecting and exploration stage to the actual mining process, AI and analytics can be used in multiple ways.

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INTRODUCTION

Data Analytics is the modern approach of data science which classify the kind of data being process now a days. As we know that now a day the data traffic became more and more rush due to advents of unstructured pattern. Hence to process such data we have to face a lot of difficulty. As the data source is get unstructured hence to process such data we need more complex algorithm. One of the best case of such complex unstructured data is 3D data which is now a day's used in the mines for coal mining. For several years, research group has been developing methods for automated modeling of 3D environments (Huber and Hebert, 1999; Huber, 2002; Huber and Hebert, 2003). In September, 2002, we were given the opportunity to demonstrate our mapping capability in an underground coal mine, the Mine Safety and Health Administration (MSHA) research mine in Bruceton, Pennsylvania. The opportunity arose as a result of the Quecreek mine accident in July, 2002, in which miners inadvertently breached an abandoned, water filled mine, trapping themselves amidst thousands of tons of water. After the miners were safely rescued, an investigation was launched to determine the cause of the accident and to identify new procedures necessary to prevent mine breaches in the future. Regulations already in place aim to prevent such an accident: mapping the mine before ending operations, exploratory drilling, and so forth. Unfortunately, old maps may be incorrect, incomplete, or simply lost. In the end, the Quecreek accident was attributed to an inaccurate map (Gibb and Hopey, 2003). A collaborative effort by several research groups at Carnegie Mellon University (CMU) has been formed to develop robots to autonomously map abandoned mines and active mines before operations are ended. Such robots would be an important contribution to mining safety. Details can be found in (Baker *et al.,* 2003; Thrun *et al.,* 2003; Morris *et al.,* 2003). In this paper, we address the problem of sensing and generating high-resolution 3D models of an active mine.

Related work

In this section, we review the most relevant work on mine mapping and localization. Early work by Shaffer (1992) described a method to localize a mobile robot in an

****Corresponding author:*** **Amar Nath Singh,**
Department of Computer Science & Engineering, Gandhi Engineering College, Bhubaneswar, Odisha, India.

underground mine by registering terrain features (corner and line segments) extracted from an a priori survey map with cross-sections from an environment map produced by a laser scanner. In (Scheding *et al.,* 1997; Scheding *et al.,* 1999), Scheding extensively tested a set of navigation sensors mounted on a Load, Haul, and Dump truck (LHD) in the harsh underground mine environment. Using the data from a laser line scanner coupled with the navigation data of the vehicle, he produced a 3D model of a section of the mine. In (Madhavan *et al.,* 1998), two line scanners were integrated on an LHD. The iterative closest point (ICP) algorithm was used to register the 2D pro_les to an existing map. This implementation was extended to mine mapping in (Madhavan *et al.,* 1998).

Figure 1. The cart-mounted Z+F laser scanner used in the data collection

abandoned mines, Thrun (Thrun *et al.,* 2003) prod uced 2D maps and partial 3D models of tunnels, using a SLAM approach with two line scanning lasers mounted on a tele-operated robot (Baker *et al.,* 2003). Several systems have been designed to map mines that are inaccessible to a ground robot, for example, by mapping a cavity using a 3D laser sensor inserted through a bore-hole. Such systems include the C-ALS (Cavity Auto scanning laser system) by Measurement Devices, Ltd. and the Cavity monitoring system by Optech, Inc.1 A similar approach has been followed in (Morris and Kurth, 2003).

Data collection

For our field test, we used a high resolution 3D laser scanner mounted on a cart as illustrated in Figure-1. The sensor, a Zoller and Fröhlich LARA 25200 (Z+F) scanner (Langer *et al.,* 2000), produces 8000_1400 pixel range and reflectance images
with millimeter-level accuracy. The field of view is 360_ _70_ with a range of 22.5 m. The laser scan head was inclined to allow higher density scanning of the _oor and ceiling near the scanning platform. Unfortunately, in some regions, the low roof was actually too close to the scan head for the sensor to fully scan the ceiling. We obtained 23 scans at three- to _ve-meter intervals along a loop trajectory through a sequence of 4 hallways (_gure 2). The cart was kept stationary at each location for the 90 seconds required to obtain each scan. Due to the capabilities of our modeling algorithms, it was not necessary to record the position or attitude of the cart. This greatly simpli_es the data collection process. The entire procedure only took about three hours, including setup and disassembly of the equipment. For this experiment, the cart was moved manually, but it would be straightforward to mount the scanner on an autonomous mobile robot.

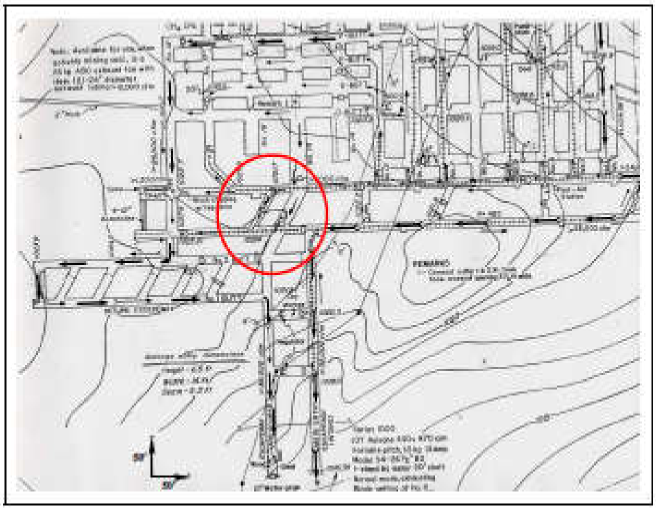

Figure 2. Surveyed map of the Bruceton mine. The red circle indicates the area mapped in our _eld experiment.

Automatic modeling from reality

Modeling-from-reality is the process of creating digital three-dimensional (3D) models of real-world scenes from 3D views as obtained, for example, from range sensors or stereo camera systems. Recently, we have developed a system that fully automates the modeling-from-reality process (Huber, 2002; Huber and M. Hebert, 2003). The key challenge of automatic modeling-fromreality is the accurate and robust registration of multiple 3D views. Although each input scan is an accurate representation of the 3D structure of the scene as seen from a single viewpoint, the data is expressed in the local coordinate system of the sensor. Our system automatically registers multiple 3D data sets in a common coordinate system without requiring any knowledge of the viewpoints from which the data was obtained. This capability is important in our case, because we did not survey the scan locations during our initial data collection. In a real system, where the sensor would be mounted on a robot, an approximate estimate of the motion between scans may be provided by the robot. Our algorithm has the ability to employ such information when it is available, but, more importantly, it will not break down when the estimates are not available.

3d View

Orginal View

3D view

Orginal View

Close-up views of the 3D model from various viewpoints (top row) and photographs obtained from the same viewpoints (bottom row).

Laser sensing in mine environments

Coal mine environments present a number of unique challenges for laser sensing systems, including the presence of explosive gas, widely ranging surface albedo, metallic objects, and wet surfaces. In the field test mine, the walls were coated non-uniformly with a white, waterproofing material, and in many places, bare coal was exposed. The roof was reinforced with metallic netting, and the environment contained numerous metallic objects, such as pipes and rails. Furthermore, regions of the walls and ceiling were wet and dripping water. For additional experiments, we collected samples of rocks and bituminous coal for analysis in the controlled environment of our laboratory. Open beam lasers can be a potential ignition source of methane gas or coal dust, but studies have shown that below 150 mW or 20 mW/mm2 methane gas or coal dust cannot be ignited by a laser beam4. With an average power of 22 mW [6], the Z+F laser poses no threat.

Our second concern was the level of noise and bias in range measurements when scanning scenes with widely ranging surface albedo. We analyzed the noise and bias using a calibration target made of 6 different color patches, including black and white. We positioned the laser at 7.5 m from the target and collected 11 identical scans to test the repeatability of the measurement. We measured the range for the pixels within each patch (725 pixels) and computed the mean and standard deviation for each patch over all the scans. Figure 7-(b) shows the distribution of range measurements for the black and white patches. As expected, the level of noise for the black target (s = 5:80 mm) is larger than that of the white target (s = 3:54 mm); however, even the worst case noise, which occurred with the black patch, was acceptable for a mine-mapping application. We analyzed reflectance-based range bias by estimating the difference in range between the white and black patch. For this experiment, we _t planes to the two patches using the total least squares method. Figure 7-(c) shows a top view of the two estimated planes, which have an offset of 1.3 cm. As with the noise error, this bias is within acceptable limits for mine-mapping. Finally, we considered the effect of scanning specular targets, such as bituminous coal (which is relatively shiny) or wet surfaces. To test this, we scanned a _at piece of coal twice . once when the sample was dry and again when wet. The sample was positioned at 7.5 m from the sensor and scanned at near-normal incidence. As expected.

Table 1.

Sample	Reflectance (min-mean-max)		
Coal (dry)	152	411	1347
Coal (wet)	26	145	486
Rock	291	491	754
Wood	4413	5663	6709
Aluminum	3330	3698	4022
Black paper	283	355	470
White paper	5353	5571	5777

Table 1: Reflectance for different targets at 7.5 m the dry sample produced erroneous range measurements associated with specular reflections. Surprisingly, the wetting the coal sample actually reduced the frequency of erroneous measurements. We hypothesize that the reason we did not experience many specular reflections in our field tests is due to the wall-coating and damp environment. Table 1 shows a comparison of reflectance values for several targets scanned at 7.5 m and near-normal incidence, including the wet and dry coal samples.

Summary and future work

In this paper, we have shown that our automatic modeling-from-reality algorithms can be successfully applied to the problem of high-resolution mapping of underground mines. The model constructed from the 23 scans obtained during our _eld test was estimated to contain geometric errors on the order of 1 cm. The results of our laboratory experiments indicate that the various sensing challenges presented by the underground mining scenario may introduce error of 1-2 cm into a 3D model. However, it should be noted that these tests are only partially representative because the environment in our laboratory and in the Bruceton coal mine do not fully mimic harsh environment of an active coal mine. The results of this paper are a proof of concept. The next step would be to further specialize our automatic modeling system for the purpose of mine mapping. First, a ruggedized platform for the system must be developed, either in the form of an electric cart or a tele-operated mobile robot. Second, our automatic modeling algorithms should be modified to operate in an online mode as opposed to the current batch method. The immediate feedback of an online algorithm would enable mine mappers to effectively plan the scan locations. Finally, we are working on new modeling algorithms that scale to very large numbers of views. Our current algorithms have $O(N_2)$ complexity in the number of input views, which limits processing to sub maps containing about 50 views.

About Author: Prof Amar Nath Singh is presently working as an associate professor as reader in the Computer Science & Engineering Department. His research area includes wireless sensor network, Underground mines, surface mining, Artificial Intelligence, Data science.

REFERENCES

Baker C., Z. Omohundro, S. Thayer, W. Whittaker, M. Montemerlo and S. Thrun, 2003. Case Studies in Robotic Mine Mapping., International Conference on Field and Service Robotics.

Gibb T. and D. Hopey, 2003. Quecreek mine accident report blames outdated map., Pittsburgh Post-Gazette, November 8.

Huber D. and M. Hebert, 1999. A New Approach to 3D Terrain Mapping., IEEE/RSJ International Conference on Intelligent Robotics and Systems.

Huber D. and M. Hebert, 2003. 3D Modeling Using a Statistical Sensor Model and Stochastic Search., IEEE International Conference on Computer Vision and Pattern Recognition.

Huber, D. 2002. Automatic Three-dimensional Modeling from Reality., Doctoral Dissertation, Carnegie Mellon University.

Langer D., M. Mettenleiter, F. Hartl and C. Frohlich, 1999 Imaging Ladar for 3-D Surveying and CAD Modeling of Real World Environments, International Journal of Robotics Research, vol 19, no 11.

Madhavan R., G. Dissanayake and H. Durrant-Whyte, 1998. Map-building and map-based localization in an underground-mine by statistical pattern matching., International Conference on Pattern Recognition.

Madhavan R., M. Dissanayake and H. Durrant-Whyte, 1998. Autonomous underground navigation of an LHD using a combined ICP-EKF approach., International Conference on Robotics and Automation.

Morris A., D. Kurth, W. Whittaker and Scott Thayer, 2003. Case Studies of a Borehole Deployable Robot for Limestone Mine Pro_ling and Mapping., International Conference on Field and Service Robotics.

Roberts J.M., E.S. Duff, P. Corke, P. Sikka, G.J. Winstanley and J. Cunningham, 2000. Autonomous Control of Underground Mining Vehicles using Reactive Navigation ., International Conference on Robotics and Automation.

Scheding S., E. Nebot, M. Stevens, H. Durrant- Whyte, J. Roberts, P. Corke, J. 1997. Cunningham, and B. Cook,. Experiments in autonomous underground guidance., IEEE International Conference on Robotics and Automation.

Scheding S., G. Dissanayake, E.M. Nebot, and H. Durrant-Whyte, 1999. An Experiment in Autonomous Navigation of an Underground Mining Vehicle., IEEE Transactions on Robotics and Automation, vol 15, no 1, 1999.

Shaffer G., A. Stentz, W. Whittaker, and K. Fitzpatrick, 1992. Position estimator for underground mine equipment., IEEE Transactions on Industry Applications, Volume: 28 Issue: 5.

Thrun S. *et al*., 2003. A System for Volumetric Robotic Mapping of Abandoned Mines., International Conference on Robotics and Automation.

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