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A Robotic System for Underground Coal Mining

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Abstract

Underground coal mining is a cooperative enterprise of powerful mobile equipment and the people who operate it. If mining equipment could be automated, the mining industry could enhance productivity, access unworkable mineral seams, and reduce human exposure to the dangerous underground mine environment. This paper describes a system that automates a continuous miner, enabling it to maneuver in highly constrained environments and cut coal without a human operator onboard. The system consists of a modified continuous miner, a laser range sensor, a SPARCstation, and control software. To date, the system has been tested on a mobile robot and on a continuous miner both above ground and in a real coal mine. This system is the first instance of an intelligent robotic system for cutting coal.

1 Introduction

Automated mine equipment could enhance productivity, access unworkable mineral seams, and reduce human exposure to the inhospitable environment of dust, noise, gas, water, moving equipment and roof-fall. Room-and-pillar mining is accomplished by repetition of a well-defined cycle of cutting coal, removing coal, and supporting the roof. Each of these operations is performed using different machines, thus allowing incremental automation of the entire mining process. This paper describes a system that automates the first step in the cycle: cutting of coal with a continuous miner.

Previous systems have controlled the miner in an "open-loop" fashion using scripts to sequence cutting operations, and manually maneuvering the machine between cuts [1]. The system had no sensors that could determine the shape of the coal.

Automation of the continuous miner's task requires the ability to maneuver the miner in highly constrained corridor-like environments, and to accurately position it for cutting coal. Our system consists of a modified continuous miner, a scanning laser range sensor, a SPARCstation, and software for autonomous control. Data from the laser range scanner is used to model the environment and to compute the position of the miner. The various cutting and loading appendages of the miner are all controllable from the SPARCstation.

The system has been tested on a mobile robot in a mock coal mine and on an actual continuous miner in a real coal mine. This system is the first instance of an intelligent robotic system for cutting coal. This paper first describes the system and each of its components, and then presents the results of system tests.

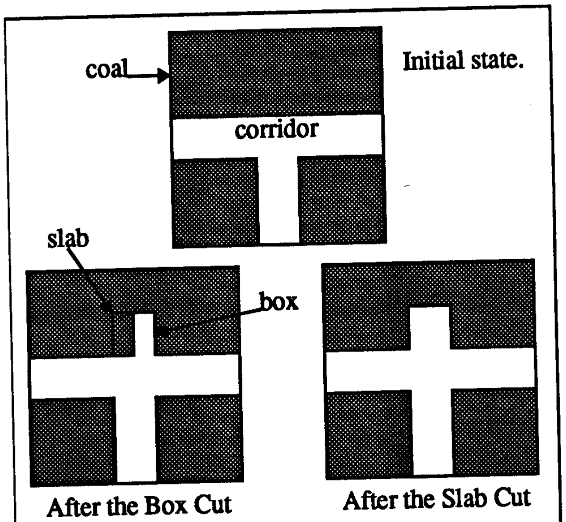

Figure 1. Extending a corridor.

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2 System Overview

The general concept of the system is simple: use a laser rangefinder to guide a continuous miner to navigate and to cut coal. In room-and-pillar mining, a corridor is extended by executing two parallel cuts: the box cut and the slab cut. See Figure 1. The miner must precisely maneuver into position before the box cut, then maneuver to reposition for the slab cut. After the slab cut, the miner must back out to make way for the roof bolter. To accomplish this advancing of the section, each maneuver is planned in advance, and the perception and control modules guide the vehicle along the preplanned trajectories to get in position and cut coal.

The system configuration is shown in Figure 2. The ovals represent software modules while the rectangles represent hardware devices. The software modules can be classified into three broad categories: planning, perception, and control. Most of the software modules are integrated through a central Task Control Architecture (TCA) [2] module, which provides communication and coordination services between modules.

The Task Planner computes the sequence of maneuvers and cuts that are necessary to accomplish a goal such as advancing the section. The motion trajectories for each maneuver are planned by the Path Planner.

The resulting task plan is executed by the control modules with assistance from perception. The vehicle control modules include the Cutter module and the Path Tracker module. The Cutter module controls the various cutting and loading appendages of the miner while cutting coal. The Path Tracker controls the locomotion of the vehicle to maneuver it between cuts. The perception modules process data from the range sensor to compute the position and heading of the vehicle as it locomotes. Two modules, the Feature-Based Pose Estimator (FPE)and the Iconic Pose Estimator (IPE) are employed depending on the navigation requirements. Each of these software modules and hardware devices is described in the following section.

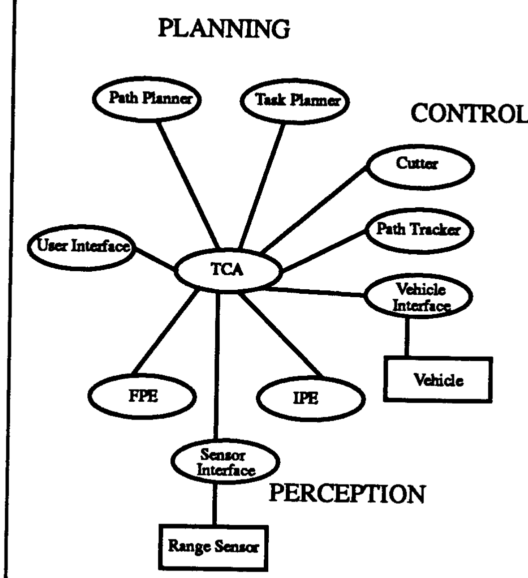


Figure 2. System configuration.

3 Planning

There are two levels of planning in the coal mining software: task planning and path planning. The Task Planner generates a sequence of subtasks consisting of miner maneuvers in open space and cuts into the coal face. The motion trajectories for maneuvers are then planned by the Path Planner and queued for execution.

3.1 Task Planning

Based on the coarse geometry of the problem, the Task Planner determines the sequence of subtasks required to advance the coal face. Two types of subtasks are employed: maneuvering and cutting. Maneuvering involves locomotion of the miner in the corridor to position for coal cutting, while cutting involves locomotion of the miner and activation of its appendages to physically engage the coal face. Each subtask is parameterized by geometric constraints on the motion of the miner, goal points to permit the fusing of adjacent subtasks in the sequence, and ordering constraints on the appendage operations. The Task Planner utilizes task tree facilities of the Task Control Architecture to assemble the subtask sequence.

3.2 Path Planning

The Path Planner module uses a line segment map of the environment to plan a safe sequence of poses for the miner to travel between an initial pose and a goal pose. A geometric model of the miner (a bounding polygon) is tested for intersections with the map during a search process to find a safe path. The search space is the set of all poses or *configurations*. The search space is three-dimensional, with each configuration in the space consisting of the miner's position and heading. A gradient descent scheme is used to find trajectories efficiently for simple cases. An A* approach [3] is employed for more difficult cases. For storage efficiency, the search space is stored as an octree. Since the complete task is composed of several subtasks queued by TCA, planning of subtask n+1 can occur concurrently with execution of subtask n, so the effective planning time is usually zero. The result of the path planner is a piecewise linear path that connects the initial point to the goal point. This path has two important characteristics: it is both *safe* and *kinematically feasible*. It is safe in that if the path is tracked by the miner properly, it will not collide with any obstacles that are in the map. The path is kinematically feasible in that the miner is physically capable of the motions required to properly track the path.

4 Perception

In order to properly track paths and cut coal, the perception subsystem must be able to measure the position and heading (pose) of the continuous miner. There are two interchangeable perception subsystems: map-based pose estimation and triangulation-based pose estimation. The triangulation-based system is much more limited in capability: it has a 35 foot maximum range of operation, and requires line of sight between miner-mounted targets and external lasers. However, the sensor that is currently used for map-based perception is not rugged enough to survive on a continuous miner, and is not explosion-proof, so until one is built, we use triangulation in our underground tests.

4.1 Map-Based Pose Estimation

Map-based perception matches range data to an a priori map of the miner's environment to compute the pose of the miner. The system utilizes two complementary map-based pose estimation methods: feature-based and iconic. The iconic method is generally slower and requires a better initial dead-reckoned estimate than the feature-based estimator. However, the iconic estimator is more accurate and does not require that the environment exhibit any predefined set of features such as corners or straight walls. The availability of two estimators enables the system to choose the most appropriate one for a given navigation task.

Both map-based pose estimation systems use data from a radial scanning laser range sensor. A typical range scan from an underground coal mine appears in Figure 3. It consists of 1000 points in a 360° horizontal planar field of view. The cross indicates the sensor position.

4.1.1 Feature-Based Pose Estimation

The feature-based pose estimation algorithm is summarized in Figure 4. For a detailed description, see Shaffer[4]. The algorithm refines an initial dead-reckoned estimate of the miner's pose to obtain a much more accurate estimate of the miner's pose. A set of predicted visible walls and corners from the map are matched to sensed walls and corners from a range scan. Once this correspondence is determined, an iterative process solves for the miner pose that minimizes the error between expected and predicted feature pairs. The quantities that are minimized are the x and y distances between corresponding corner locations, and the radial distance and orientation difference between corresponding line segments (walls).

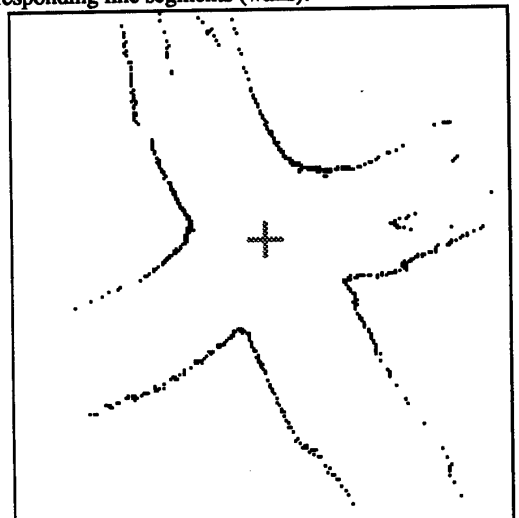


Figure 3. A range scan from a mine.

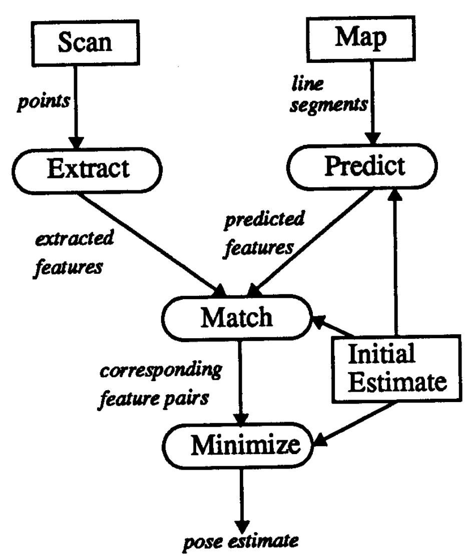


Figure 4. Feature-based pose estimation.

4.1.2 Iconic Pose Estimation

The iconic pose estimation algorithm is summarized in Figure 5. For a detailed description, see Gonzalez[5]. The iconic estimator operates on similar input to the feature-

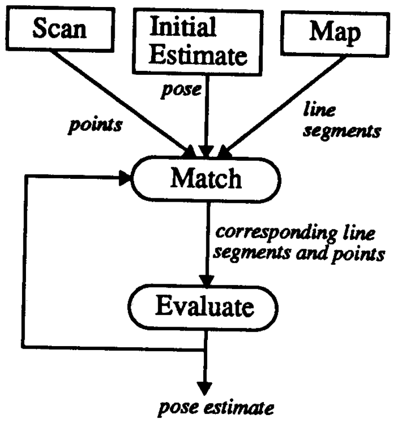


Figure 5. Iconic pose estimation.

based estimator: an initial pose estimate, a range scan, and a map. The differences are that the map consists of possibly short line segments which can approximate any geometry of the environment, and the dead-reckoned estimate must be more accurate so that the algorithm will converge. Range data points are matched to line segments from the map, based on minimum distance. The miner pose that minimizes the distance error between the range points and their corresponding line segments is computed. Based on the new pose, the correspondences are updated. This process repeats until the change in total distance error falls below a threshold.

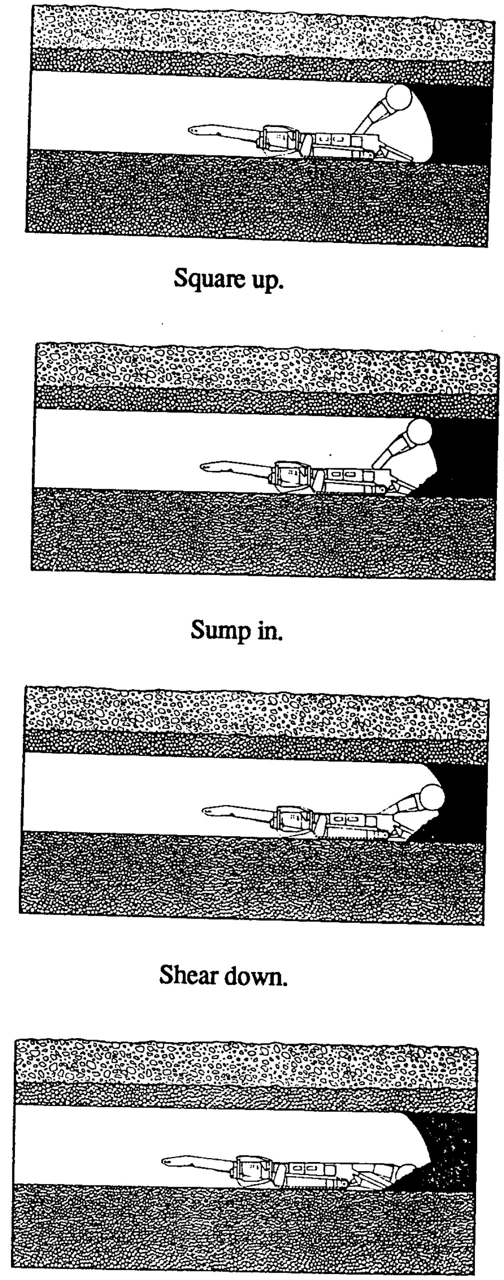
This algorithm differs from the feature-based method in that it matches *every* range data point to the map rather than condensing the range data into a small set of features to be matched to the map.

4.2 Triangulation-Based Pose Estimation

The CMU range sensor, the Cyclone[6], does not meet the requirements for operation on a continuous miner (ruggedness, explosion proof, etc.), so our underground tests have used an alternate pose estimation system. Lasernet is a commercially available system which consists of a scanning laser and a reflective target. Using two externally mounted lasers, and two miner-mounted targets, the pose of the miner can be determined accurately to a maximum range of about 35 feet. The Cyclone is vehicle-mounted, and therefore does not have a limited range of operation. For details on the triangulation-based system, see Anderson[1].

5 Control

The continuous miner must be controlled to execute two types of operations: coal cutting and maneuvering between



Square up.

Sump in.

Shear down.

Remove cusp.

Figure 6. The sump-shear cycle.

cuts.The miner is a tracked (skid-steer) vehicle that has a large rotating cutter head on the front and a conveyor from the cutterhead to the rear of the machine.

5.1 Cutting

The coal cutting cycle consists of four steps: squaring up to the coal face, sumping in, shearing down, and removing the cusp. (See Figure 6.) This cycle is repeated until the desired depth of penetration into the wall of coal is achieved. Squaring up refers to aligning the miner with the desired heading of the cut. For the initial sump, this is accomplished by driving the miner into the wall, letting the tracks continue to drive after impact, and stopping when the heading has reached the desired value.

Sumping in means turning on the rotating cutterhead and driving into the wall of coal. Shearing down involves stopping the tracks and allowing gravity to pull the rotating cutterhead down through the coal until it reaches the floor. Due to the cylindrical shape of the cutterhead, there is a "cusp" of coal left on the floor. Cusp removal is the process of driving the machine backwards with the cutterhead spinning to shave off the cusp.

The cutting aspect of the control is straightforward: sequence the appendages in the proper order, and repeat the cycle until the perception system (the pose estimator) confirms that the desired depth of cut has been accomplished.

5.2 Maneuvering

Control of the continuous miner during maneuvering is the responsibility of the Path Tracker. The module is an implementation of the "pure pursuit" algorithm [7]. At each time interval, the current position and heading of the vehicle are sensed, and a trajectory that will intersect the desired path at a desired lookahead distance is computed. The correction trajectory usually consists of an arc followed by a straight line, but if the vehicle is far off the path, a turn-in-place might be required. Since the miner is currently capable of only one turning radius other than zero, some corrections would be impossible without turning in place. The cruising speed of the miner is about three inches per second, and the minimum time interval between corrections for stable control is a few seconds.

6 Results

The system was tested in three environments: an indoor mine mock-up using the Locomotion Emulator (LE) mobile robot, a pseudo-coal corridor using a Joy CM16 continuous miner, and a real underground coal mine using a Joy CM14 continuous miner.

For the first test setup (shown in Figure 7), a wooden frame with the dimensions of a continuous miner was attached to the LE, and the LE controller emulated the skid-steer continuous miner. The Cyclone range sensor was mounted on the LE along with a SPARCstation. The system successfully maneuvered through a wooden mine corridor mock-up, and simulated the coal cutting cycle.

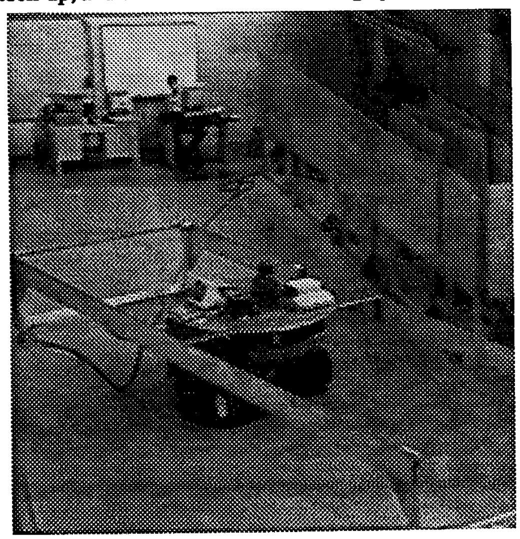


Figure 7. LE test setup.

The second test setup (shown in Figure 8) involved a real continuous miner (Joy CM16), and a more realistic mine mock-up. The spinning cutterhead sumping into the pseudo-coal is shown. The Cyclone sensor could not be used since it is not rugged enough to be mounted on a continuous miner. Instead, the Lasernet system provided the needed position and heading feedback. The mine mock-up

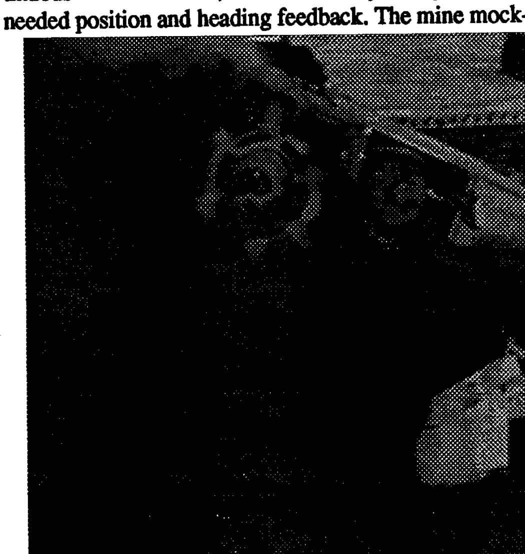
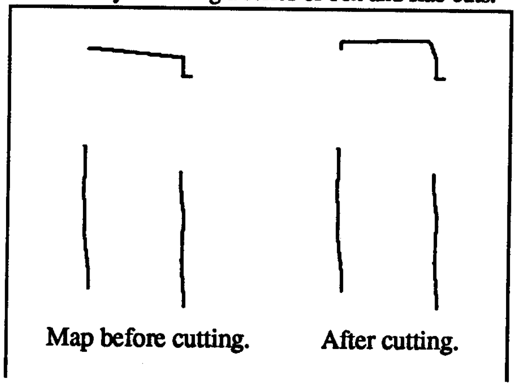


Figure 8. CM16 cutting pseudo-coal.

was more realistic in that it was a poured block of imitation coal that allowed us to test the cutting software. This environment was still ideal in that the floor was flat concrete instead of bumpy rock.

The third and ultimate test setup was in a real underground coal mine using a Joy CM14 continuous miner and the Lasernet sensor. (See Figure 9.) The SPARCstation was off-board the miner and connected through a single serial line. The system successfully extended the mine corridor several feet by executing a series of box and slab cuts.



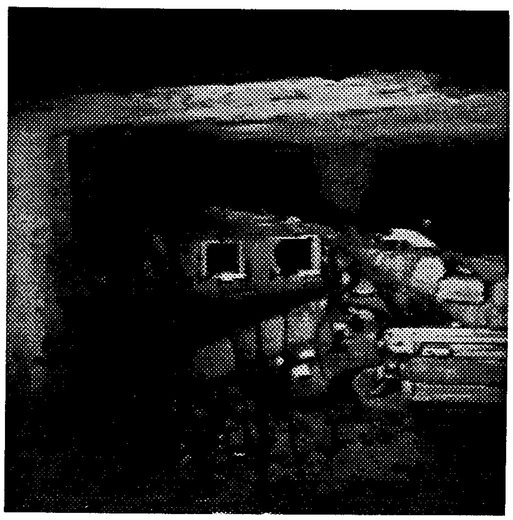


Figure 9. CM14 engaging real coal.

7 Summary

A robotic system for automating a continuous miner was presented. A laser range sensor was used to guide the vehicle while maneuvering in tight corridors and positioning for coal cutting. The system succeeded in initial tests in the lab and in the mine. In contrast to previous script-based systems, this work is the first instance of a robotic system with potential for fully automating a continuous miner.

8 Future Work

The work described in this paper is preliminary. Additional work is needed to make the system more robust and to permit long-term operation without human intervention. Future research directions include obtaining a hardened Cyclone-type sensor so we are freed from the maximum range imposed by the Lasernet system, and we can update maps of the mine as new coal is cut. Furthermore, we will begin automating the remaining machines used in room-and-pillar mining, including the shuttle car which hauls coal from the continuous miner to a conveyor belt, and the roof bolter which reinforces the roof in a newly-mined corridor.

9 Acknowledgments

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