Reactive navigation and opportunistic localization for autonomous underground mining vehicles

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Abstract

This paper describes an autonomous navigation system for a large underground mining vehicle. The control architecture is based on a robust reactive wall-following behaviour. To make it purposeful we provide driving hints derived from an approximate nodal-map. For most of the time, the vehicle is driven with weak localization (odometry). This need only be improved at intersections where decisions must be made – a technique we refer to as opportunistic localization. The paper briefly reviews absolute and relative navigation strategies, and describes an implementation of a reactive navigation system on a 30 tonne Load-Haul-Dump truck. This truck has achieved full-speed autonomous operation at an artificial test mine, and subsequently, at a operational underground mine.

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1. Introduction

Mining is an important global industry that has so far exhibited a slow uptake of robotics and automation technology – but this is beginning to change. The main driving forces for this industry are a need for increased productivity, societal demands for safer workplaces, an aging work-force, and declining value (in real terms) of its products. To date, productivity increase has been achieved through mechanisation, moving from human and animal power early last century to present-day electric and diesel powered machines. Machines have become progressively larger and more powerful but practical limits are reducing the rate of growth. Automation has been identified as the most likely means to attain the next quantum jump in productivity and safety since sensing, control and computing technologies are advancing rapidly.

In underground mines ore is fragmented by blasting in voids known as stopes. Manually operated articulated wheeled vehicles known as Load-Haul-Dump or LHD units (Fig. 1) are typically used to move (or tram) ore from the stope to a crushing plant or truck. Rock stresses in the stopes make rock-falls likely thus for safety reasons they are inaccessible to humans. Therefore, within the stope the LHD must be operated by tele-remote or line-of-sight remote

Fig. 1. Our experimental Load-Haul-Dump truck.
control. In the latter case, this necessitates the driver having to alight the vehi-
cle each cycle which contributes to increased cycle time and the potential for
accidents. For these reasons, some mines are now tele-operating [1] the vehicles
for the entire cycle. While they have gained in safety, they have often lost
productivity compared with manned LHDs. The sensory perceptions of a tele-
remote operator are quite limited and this has a marked effect on the ability to
drive quickly.

The full or partial automation of LHDs is therefore a very attractive
proposition to the industry. There is the potential to increase productivity
above tele-remote and remote control levels while simultaneously improving
safety by removing people from the vehicles altogether. One remote operator
could conceivably control or “manage” a small fleet of largely autonomous
LHDs. The operator need not even be underground at the mine, but could
work in an office in a major city. To be cost effective it is not necessary for the
vehicle to be faster than a manned one – the benefits come from reducing the
number of operators, working through breaks and the maintenance advantage
of operating within the machine’s design envelope.

1.1. Indoors or outdoors?

Research within the mobile robotics research community can be divided into
indoor or outdoor environments – there is a wealth of research into mobile
robotics in both application areas. It is therefore useful to consider whether the
underground mining environment is indoors or outdoors in the robotic sense.

The outdoor mobile robot environment is typically characterised by rough
terrain, with knowledge of vertical elevation required in order to plan a path.
Planetary rovers [2] are typical of this class. On the other hand, the indoor
environment comprises rooms, corridors and a planar floor. Many of the
navigation techniques developed by researchers for indoor applications treat
the world as a 2D environment. Typically they employ sensors to follow the
walls and look for openings (doorways) to move through. Because the walls are
smooth, flat and vertical it is possible to assume that the space that the sensors
see at a height of say 1 m above the floor also exists at ground level and hence a
robot can traverse the floor safely.

The underground environment is closest to the indoor mobile robot envi-
ronment. Tunnels in underground mines are somewhat like corridors in an
office building in that they have a floor, ceiling and walls. The floor of mine
tunnels are generally dirt (mud) roads not smooth and flat like those of an
office corridor. Generally each level of the mine can be considered as a hori-
zontal plane, though spiral ramp roads are often used to link different levels.
Most tunnels have an approximately rectangular cross-section and hence many
of the navigation techniques developed for the indoor robotics environment are
applicable to underground mine vehicles. Maps are readily available at all
underground mines making the indoor comparison even stronger. The aim of this paper is to consider the application of indoor robotics techniques to the automation of underground mining vehicles.

In this paper we will show that the task of LHD navigation can be achieved using classical wall following techniques. We will also argue that it is not necessary to know the location of the vehicle with any precision. The classical question “Where am I?” can be answered simply by “In a tunnel!” We need to know nothing more than the identity of the next intersection – a concept we refer to as opportunistic localization. This makes sense from everyday human experience where we drive to an unfamiliar location, not by following a trajectory of spatial coordinates, but by a road-following behaviour combined with recognition of intersections at which appropriate decisions are made.

1.2. Paper outline

The remainder of this paper is structured as follows. Section 2 reviews the state-of-the-art in vehicle navigation concentrating in the area of underground navigation and comparing and contrasting absolute and reactive navigation techniques. Section 3 describes our project in some detail, and Section 4 presents some results from trials conducted at an artificial test mine, and subsequently at an operational underground mine. Section 5 contains a discussion on absolute versus reactive navigation for this application. Finally, Section 6 summarises our achievements and conclusions.

2. Navigation for LHDs

The first generation of Autonomously Guided Vehicles (AGVs) were developed in the 1960s, 1970s and early 1980s. These AGVs followed rail-type guides placed in the environment to aid navigation, for instance following wires buried in, or lines painted on, the floor. Other robots used a rotating laser to measure the bearing angle to fixed reflective strips distributed around the work environment. Robots like these are now in common use around the world for factory type situations where speeds are low, floors are smooth and flat, and more importantly, where the route or routes remain fixed for long periods of time (sometimes years) and can thus justify the expenditure on installation and continued maintenance of navigation infrastructure.

2.1. Absolute navigation

A common navigation technique used in both the indoor and outdoor environments is that of absolute navigation. Here, the absolute position with respect to some fixed real-world coordinate system is known at all times. A
path for the vehicle is given in the same coordinate system and the vehicle attempts to maintain the desired path as accurately as possible. The control problem is to use the estimated pose to keep the vehicle following the predetermined path in the map. Examples of path following control for LHDs may be found in [3,4].

Localization is the process of estimating the absolute position of the vehicle. It is typically achieved by fusing data from on-board sensors and external measurements. Internal sensors (such as inertial measurement, odometry and heading angle, etc.) are subject to scale errors and offsets which lead to unbounded errors on the position estimate. These must be periodically corrected by means of an external absolute position measurement such as from GPS in the case of outdoor vehicles, or from the detection of artificial beacons (e.g. retro-reflectors or radio transponder tags) or natural features (e.g. unique tunnel profiles if using a laser scanner, etc) in the case of indoor vehicles. The Kalman filter is perhaps the most common framework for data fusion.

Makela et al. [5] described a navigation system for an LHD which used dead reckoning (incorporating odometry, a ground-speed radar and a fibre optic heading gyro) which was periodically corrected at least every 50 m using passive LC resonators or retro-reflective circles attached to the roof (detected by a row of optical switches).

In 1997 Q-Navigator [6] tested their system, based on a bearing laser scanner and retro-reflectors, on an LHD in Kiruna mine, Sweden. They used odometry and an articulation angle encoder, but no heading gyro. They successfully demonstrated full automatic driving of the LHD at the vehicle’s top speed (22 km/h). The Q-Navigator system was based on a navigation system by NDC for AGVs that has been installed on more than 700 AGVs in factories around the world since 1991.

Madhavan et al. [7] proposed an absolute localization system that achieved position correction without the use of artificial beacons. They used a map consisting of short line segments which approximated the geometry of the tunnel walls. The map was constructed using a 2D laser range finder and the same laser was used to generate on-line tunnel profiles to match to the map.

A fundamental failing with these traditional absolute navigation methods is that they are actually “blind” to their environment. Instead of “looking” around and “seeing” where to go, they rely totally on the fact that their estimated position is very accurate and that the path that they are following, which is derived from a pre-existing map, is also accurate.

The logical conclusion of the absolute navigation paradigm is Simultaneous Localization and Map Building (SLAM) or Concurrent Mapping and Localization (CML). Here, no a priori map is required, the map is generated as the robot moves around the world for the first time. Thrun et al. [8] demonstrated a robot that navigated its way around a museum using a SLAM based navigation system. The system built 2D maps of the museum as it moved around.
3D SLAM systems [9] have also been demonstrated recently. SLAM is currently the topic of much research but has not been implemented in the underground mining environment.

2.2. Reactive navigation

A simple type of navigation which has been used since the 1960s is that of reactive navigation, in which an AGV simply reacts to something in its immediate environment in order to continue moving forwards. Such systems tightly couple the sensor(s) with the steering actuators at a very low-level. An example is the warehouse AGV that follows a painted line on the floor – little “intelligence” is required. Similar systems, using retro-reflective lines, or lines of lights, on the ceilings of tunnels have been tested in mines [10,11] and some are available commercially. These typically use CCD cameras to detect the relative position of the line immediately above, or slightly ahead of the vehicle. Such a configuration provides almost no look-ahead with the consequence that heading changes cannot be anticipated. It is analogous to driving your car and following a line on the road by looking through a hole in the floor! For high-speed driving such as for IVHS applications the camera looks forward so as to maximize look ahead [12,13].

In the case of an LHD, the essence of the driving task is to stay in the middle of the tunnel and not hit the walls. This is an application of wall following which has been popular with the indoor AGV community for the past decade. Many of the robots used ultrasonic sensors, laser rangers or radar for wall detection. Wall-following techniques based on ultrasonic [14–16] sensors have been described for underground mining applications.

Significant look-ahead is essential and we use a scanning laser range finder to sense the walls ahead of the vehicle.

Reactive navigation is a form of “active perception” [17] whose central tenet is that instead of consulting a model of the world, the robot should consult the world with appropriate sensors. For the robot to move through the environment, it does not need to “know” with any accuracy where it is in the environment with respect to some global co-ordinate frame. It only needs to “know” where it is relative to objects in its immediate vicinity, i.e. a relative navigation approach compared to the absolute navigation approach discussed above.

Two techniques that seem suited to wall-following in the underground mining environment are potential field and neural network methods.

2.2.1. Potential field methods

Potential field methods for navigation have been described by robotics researchers since the 1980s [18]. The general principle is to treat the vehicle as a particle that is attracted by a potential field radiating from its goal and repulsed by potential fields radiating from obstacles. A local path plan may then be
formed by applying a force, based on the sum of the potential fields, to a
general desired path whose end is fixed to the vehicle. Such schemes are nor-
mally iterative in nature and are hence amenable to real-time implementation.
A limitation is that the vehicle may become trapped in a local minima and be
unable to reach its goal.

Asensio et al. [19] developed an AGV based on the Labmate robot that used
a potential field method to move around an office environment. Their system
used a scanning laser rangefinder to detect the walls and perform wall-following. Scheding et al. [20] described a local path planner based on a popular
potential field method. The local path was created by applying the summed
potential field to a straight line segment that began at the vehicle and pointed in
the direction of the goal. Such potential field methods are very similar in
principle to the active contour methods described by Blake and Isard [21] which
are commonly used in image processing and computer vision applications to
segment scenes.

2.2.2. Neural network methods

Neural networks can also be applied to the wall-following problem. Being
fast to execute they are appropriate for use on high-speed AGVs. Pomerleau
[22] described how a vehicle was taught to steer using a neural network. An
association between sensor data and steering angle was made which allowed
the vehicle to steer through previously unseen terrain. Learning in this case
took place off-line. Dubrawski and Crowley [23] presented a neural based
navigation method that enabled an AGV to learn on-line using a trial-and-
error method. Their AGV was equipped with 24 ultrasonic range sensors and
an odometer. A goal position was set by a human supervisor or by an external
path planner.

2.3. Which way do I go?

Reactive navigation systems do not perform any path planning at the global
scale – a pure wall-following LHD will move along the tunnel until it en-
counters a dead end (where it will stop). In order to become purposeful, that is
to be able to complete a useful mission, it needs to decide how to reach its goal.
In a tunnel environment the decision process is quite limited. In general there is
only the choice to go forward or backward, but at an intersection there is a
choice of which path to take. This then leads to two subproblems:
1. Which intersection is this?
2. What action to take?

The structure of these decision points makes their detection easy [24]. There are
two solutions to this problem both based on human methods:

1. **Absolute position information and a map.** If an AGV has a global map
   of the mine and it has localization information, then it is possible to make a
decision. Note that localization accuracy does not need to be high, but only good enough to determine that it is approaching junction A, or junction B from a particular direction. The human equivalent of this situation is being given a map of a city and being told where you are and where to go. Beacons such as radio tags or bar codes located near the decision points (normally intersections) can be used to obtain absolute position information. Natural features may also be used as localization beacons. Asensio et al. [19] demonstrated an AGV that could move around offices and through doorways while avoiding obstacles in its path. They used a scanning laser rangefinder to determine the position of the AGV with respect to the doorway and hence reset any drift accumulated during odometry based position estimation.

(2) A relative route. An AGV can be given a sequence of instructions in order for it to reach its goal. For example, it may be told to drive 100 m and turn left at the next T-junction, continue for 230 m and turn right at the next intersection, and finally stop after 50 m. This method is analogous to the way in which humans verbally describe a route to another person. Such a technique was used by Tsubouchi et al. [24] to guide a vehicle in an office building environment. They used laser scanners to perform low-level reactive wall-following.

2.4. Discussion

Both absolute and reactive navigation techniques have been, and are being, developed to guide autonomous vehicles in mine tunnels. Absolute navigation techniques that rely on detailed a priori maps are probably not viable in the mine tunnel application. By their very nature, mines change every day and so to rely on a potentially old map is hazardous. SLAM techniques provide a nice solution in that maps are generated and update continuously. In this respect SLAM is bringing active perception concepts into the absolute navigation framework. However, SLAM systems are in their infancy and have not been tested in the mining environment yet. A very real problem is with long straight tunnels which provide no natural topographical features to detect and track.

The reactive wall following navigation systems described above have a significant advantage over the reactive rail guide following approaches in that they have the potential to operate with no guidance infrastructure (apart from the walls). This leads to lower installation and maintenance costs which can be significant over large areas of a mine. However the low-level reactive wall-following behaviour must be augmented with a purposeful strategic behaviour in order to accomplish useful missions. All of this can be achieved with only occasional knowledge of position, i.e. opportunistic localization.
3. Implementation

3.1. Project history

In 1996 we conducted a number of field trials at a mine in Queensland, Australia [25]. Data were collected from a number of sensors mounted on an LHD with the aim of determining which sensors performed best underground. It was found that the 2D laser scanner was an ideal primary navigation sensor in the underground environment. In July 1998 we began an industry funded project to develop an autonomous navigation system for an LHD which was field tested in July 1999.

3.2. Automation architecture

We were fortunate in being able to “piggy-back” the automation system onto an existing tele-operation system which provides an excellent substrate for automation since:

• there is only one point of control;
• the electrical interface necessary to control the vehicle already exists;
• the safety systems build into the tele-operation systems can be used; and
• the vehicle can be switched back to the underlying tele-operation mode for:
  ø operations that have not been automated (i.e. digging) or;
  ø for vehicle recovery if the automation system fails.

Our automation system comprises three functional layers:

Strategic layer determines when and where the vehicle will perform an action based upon a list of hints – defined by the selected route. To do this, the strategic layer must be able to estimate the approximate position of the vehicle. This knowledge is used to influence the behaviour of the vehicle through hints (i.e. driving and turning strategies) which are passed down to the tactical layer. Since this layer has some expectation that it is approaching a node, e.g. an intersection, it can use this knowledge to assist in its recognition.

Tactical layer obeys strategic driving hints and actually “drives” the vehicle while avoiding the tunnel walls. The desired vehicle path is estimated with active contours that follow the walls. The tactical layer has no knowledge of the location of the vehicle with respect to a global coordinate frame, it simply senses and reacts to the walls. It sends steering and speed set-points to the operational layer.

Operational layer contains the control loops that convert steering and speed set-points into low-level machine input signals that control functions such as throttle, gearbox, brake and articulation joint hydraulic rams.

This control architecture allows various modes of operation (Fig. 2). The original mode of operation is the manual mode, where the vehicle is controlled
by an operator who is sitting in the driver’s seat. The second mode is the remote mode, where the vehicle is controlled with a joystick via a tele-operation system. In the first of the computer controlled modes, the drive-by-wire mode, the operational layer accepts speed and steering set-points from the operator and hides the actual dynamics of the machine. In the co-pilot mode, the tactical layer controls both speed and steering of the vehicle. The operator acts as a co-pilot and provides hints to the tactical layer which will influence behaviour at decision points. And finally, in the autonomous mode, the strategic layer interprets a mission and generates the appropriate hints to the tactical layer, which in turn generates the appropriate speed and steering demands to the operational layer. The vehicle is given a mission by the operator, who subsequently, has no influence over the vehicle’s driving behaviour.

3.3. Development environment

Our development environment includes a 30 tonne LHD (Fig. 1) and an artificial test mine constructed from shade-cloth (Fig. 3). The roadway is 300 m in length and contains curves, sharp corners, a loop and a large “room” (simulating an underground workshop). The shade cloth walls are opaque to the lasers and transparent to radio frequencies. Thus it was possible to develop the system using a standard low-cost wireless high-bandwidth local area network (LAN).

3.4. Missions, routes and nodes

To perform useful tasks, the vehicle must perform a sequence of actions. We call this sequence of actions a mission. Missions are loaded and monitored remotely using the mission control interface (Fig. 4).
Fig. 3. Layout of the test mine.

Fig. 4. The mission control interface.
The three main types of actions that the vehicle may perform are
• driving (along a route),
• dumping ore (at the end of a route) and
• digging ore (at the end of a route).

A nodal-map of the mine can be constructed from a traditional map of the
mine, or it can be constructed by driving the vehicle along the path and ob-
serving the local environment. Nodes are typically identified as points that have
obvious natural features. A nodal-map of our test track is shown in Fig. 5. Here
the nodes are represented by circles and the lines that link nodes are called
segments. A route is defined by a list of nodes that the vehicle must pass
through. For example, the route from the start of the track to the stop-log via
the loop would be defined by the list of nodes: N1 N2 N3 N4 N5 N5 N4 N3 N2
N6.

To assist the tactical layer, the route also contains a number of hints. These
hints are only appropriate along specific sections of the track. After driving the
LHD in co-pilot mode a few times it is possible to estimate the optimal driving
strategies. This is analogous to creating pace notes for rally driving.

3.5. Odometry

We use odometry to provide an estimate of distance travelled along each
segment (path between one node and the next). This is used to
(1) give some indication of distance remaining to the next node, and to
flag an error if the expected node has not been found within a certain toler-
ance,
(2) schedule driving hints such as maximum speed, keep left, keep right, etc.

Odometry is a sensor that is poorly regarded within the outdoor mobile
robotics literature. While the problems of slippage and wheel radius estimation

![Fig. 5. Nodal map of test mine.](image-url)
are real, the difficulties are perhaps exaggerated. For our application, a 30 tonne vehicle, operating on dirt roads we have found odometry errors to be less than 1%. Our odometry is based on drive shaft rotation and calibrated to distance travelled. Clearly this calibration will change with time but a simple learning rule, based on odometer reset errors, could be used. This is in contrast to approaches such as [26] where ‘wheel radius’ is estimated online, but also includes lumped model error.

4. Experimental results

4.1. Test mine results

To test the performance of the autonomous LHD, a mission was constructed that simulated a typical job of an LHD in a real mine. The mission consisted of a route from a digging position to a dumping position, followed by a dumping action, which in turn was followed by the reverse route from dump to digging positions. The forward (dig-to-dump) route is shown in Fig. 5. Fig. 6 shows the dig-to-dump route in a series of “snap-shots” constructed from the laser data.

During a mission the odometry of the LHD was automatically corrected at each node. The size of the correction ranged from a few centimetres (when the LHD was travelling slowly) to a few metres (when the conditions were muddy with increased wheel slip, or when the vehicle was travelling very quickly and the wheels became airborne).

To gauge the performance of the automated LHD it is useful to compare it to a human driver performing the same mission. A comparison between the speed of the vehicle under manual and automatic control is shown in Fig. 7, where the range (x-axis) is defined as the distance from the starting position. In the upper plot the vehicle travels in the forward direction, i.e. the speed is positive and the vehicle moved from 0 to 300 m, while in the lower plot the vehicle travels in the reverse direction, i.e. the speed is negative and the vehicle moves from 300 back to 0 m. From this comparison a number of points can be made:

- In the first 25 m, as the LHD turns the first sharp left-hand corner, its speed was fixed at 5 km/h, while the human driver took a more aggressive speed of 10 km/h.
- Once the corner was successfully negotiated, the LHD was driven at maximum speed. The actual speed was determined by the ground conditions. There was very little difference in the speed between manual and automated control.
- At the final corner, the LHD must be prematurely slowed for the front laser to see the corner and be given enough time to act.

A comparison between the steering of the vehicle is shown in Fig. 8, from which the following observations can be made:
At 20 and 280 m the LHD articulated to full left lock as it negotiates the 4WAY intersection in both manual and automatic runs.

At 150 m the LHD articulated 20° to the right around the back of the loop in both manual and automatic runs.

Along the straight sections there was considerable oscillation in both manual and automatic runs. This was due to the rough nature of the track.

In the forward direction (upper plot) the first left-hand turn was taken earlier by the human driver, while the last turn was taken at the same range.

On the return route (lower plot) the situation was reversed. The first right-hand turn was made at the same range, while the last right-hand turn was made late.

The delay in turning is related to the interpretation of free space by the tactical (wall-following) layer and by the fact that the laser cannot see around...
the corner. This delay limits the speed at which the automation system can be used around such sharp corners.

Fig. 9 shows the clearance between the LHD and the tunnel wall for the cases of manual and automation operation, from which the following observations can be made:

- The noise in the range data was due to either holes in the shade-cloth, or reflected light from dust.
- The difference in the horizontal position of features (i.e. entrance to workshop) was due to slip and the orientation of the LHD.
- At 150 m, in the forward direction, the LHD under manual control tended to hug the left-hand wall of the loop, while the automated system remained in the centre of the tunnel.

To summarise, the LHD was reliably driven along a 300 m route, which included two 90° corners and a sweeping loop with a radius of curvature of less than 8 m, at speeds up to 18 km/h. The vehicle has operated for over an hour at a time without any human intervention.

Under most conditions the LHD was driven autonomously at the same speed as a human operator. Subjectively, the LHD under autonomous control takes a better line, and reacts faster than a human operator. The only weakness occurs at sharp intersections where the autonomous LHD must travel slowly to “see”
around the corner. An experienced human driver can drive more aggressively around a blind corner because they can remember the profile of the tunnel from a previous run. This is a small penalty to pay for having no map, however some form of local map of each intersection could be added and learnt online.

4.2. Underground results

The second phase of the project was to establish whether the vehicle would perform in the same manner under operational conditions. For this series of tests, the LHD was transported to an operational underground mine. The mission control computer was connected to the existing mine communications infrastructure (leaky feeder\(^1\)). The system was up and running in less than two days. A section of tunnel, 150 m in length was isolated for the test. For half a day the vehicle was driven up and down the test tunnel to acquire data to generate the relevant driving hints. In the main test the vehicle drove autonomously for an hour, periodically switching back to the tele-remote system to dig and dump

\(^1\) A 1200 baud RF communications system.
ore. At one stage a Palm Pilot was used to enter driving hints, demonstrating the simplicity and independence of the control communications. During the demonstration a video record was taken from the LHD. A number of snapshots are shown in Fig. 10, where the LHD is shown stopping in front of a draw point (where ore is loaded). In the second figure, the LHD has just stopped short of the ROM bin (where ore is dumped). The route was over 100 m in length. At no stage during these underground trials did the LHD touch the walls.

Fig. 9. Distance to walls at high speed.

Fig. 10. Video capture from on-board cameras: (a) LHD at draw point; (b) LHD at ROM bin.
5. Discussion

To reiterate, both absolute and reactive navigation techniques have been, and are being, developed to guide autonomous vehicles in mine tunnels. Traditional approaches to absolute navigation (non-SLAM approaches) are blind to their environment – the control of the vehicle is inferred from the position of the vehicle, rather than what the sensors tell it about the position of the walls. Such techniques are therefore highly dependent on the accuracy of both the localization and the map – any error may cause the vehicle to collide with a wall.

Reactive navigation is far more robust since the vehicle is controlled by the actual free space perceived in front of the vehicle. The vehicle is able to move at high speed without any knowledge of its global position, however such knowledge is essential if the vehicle is to be purposeful and choose the appropriate path at an intersection. Opportunistic localization implies the vehicle knows only the segment of the route on which it is travelling and the identity of the next node. Furthermore, knowledge of the vehicle’s position allows the vehicle to operate at speeds higher (or lower) than the free-space would recommend (e.g. on long curves, or bumpy terrain).

The split between control and localization highlights one of the main differences between absolute and reactive navigation. Using absolute navigation, vehicle control can only be achieved after the vehicle’s absolute location has been established. The two routines are tied together; they are synchronous. The vehicle cannot be controlled if there is a problem with localization. In many situations, the task of localization can be very difficult. It can be computationally expensive and requires an excessive amount of redundant information to make it robust. To improve the reliability of finding landmarks, infrastructure is added to the environment (e.g. reflecting beacons).

On the other hand, with reactive navigation, vehicle control and localization are “decoupled”, the vehicle control can run independently, and at a much higher bandwidth than the localization. This is critical for high-speed autonomous vehicles. In practice, vehicle control is a low-level process performed at a high bandwidth, while localization is a high-level process performed at a much lower bandwidth. Since localization is not critical to vehicle control, then its reliability and robustness is less important. It may even be possible to have no localization infrastructure, and in this application we use the intersections themselves as landmarks.

6. Summary

The results so far are very promising. Our autonomous LHD is close to the performance of a human operator around our test mine. The system has also been successfully demonstrated underground at a real mine. Again, the vehicle
was able to operate at full-speed through a typical production cycle without localization infrastructure or physical changes to the mine tunnels.

In the trials that we have conducted, we have shown that:

- reactive navigation can control a high-speed mining vehicle,
- opportunistic localization is sufficient to navigate underground,
- under most conditions our system can equal the performance of a human operator,
- it can operate with no localization infrastructure, and
- 2D scanning lasers are currently the sensor of choice.

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