# Laser Based Intersection Detection for Reactive Navigation in an Underground Mine

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***Abstract*— In this paper we propose a new feature detection algorithm to enable junction recognition intended for high speed reactive navigation in tunnel like environments. We also present an extensive experimental evaluation of the algorithm based on data recorded in a real mine. The algorithm is faster and has less environmental constraints than similar algorithms that can be found in the litterature.**

## I. INTRODUCTION

Today the use of mobile robots is accepted as a part of everyday life. Autonomous vacuum cleaners and lawnmowers are examples of products which are available for home use. In industry, large efforts are made to replace manually operated vehicles in dull or hazardous applications with autonomous or teleoperated vehicles. One example of an industry application is the LHD (Load-Haul-Dump) vehicles, Figure 1, which are typically used in mines to transport ore from the stope or muck-pile to a dumping point. The work presented here is a part of an effort to develop an autonomous navigation system [1], based on fuzzy behaviours, for LHD vehicles in underground mines.

The requirements for navigating the tunnels of a mine are similar to the requirements for navigating corridors of an office building. Firstly, the robot has to be able to locate the walls of the corridor that is currently being traversed. Secondly, intersections or doors have to be identified and their locations relative to the robot have to be established. In the mine application there are also additional requirements: The vehicle has to be able to travel at a high speed (20 – 30 km/h), which adds restrictions not only to the execution time of the algorithms but also to the detection range. Further on, in certain mine types intersections occur frequently, see Figures 5 and 8, which adds extra requirements to the navigation system and in particular to the intersection recognition. The distance between intersections in a mine tunnel varies between a only few meters up to 50 m or more depending on mine type. Finally, in most mines the surface of the tunnel walls is rather rough and irregular, which makes it difficult to rely on wall detection to recognize junctions.

Forsberg et al. [2] and Barber et al. [3] describe functions to detect open doors in data from laser range scans. Both methods are based on evaluating line segments detected by Hough Transform of the laser data. Diaz et al. [4] use a method where the laser scan data is aligned to the previously detected corridor. A box filter is then applied along each wall to detect regions with zero laser readings, which indicate openings in the walls. Methods using a learning approach to detect topological structures such as corridor intersections and open doors are described by Kulyukin and Gharpure [5]. In the mine navigation application both Duff et al. [6] and Polotski et al. [7] have described navigation systems based on topological structures. However, neither describes the technique used for feature detection.

All methods above require that either the lines of the tunnel walls are detected, or that the sensor data is transformed and aligned to the direction and location of the detected corridor. Unfortunately we cannot make the assumption that the walls will be straight in the target environment, a mine, and as a consequence none of the found methods are applicable. The key to robust detection of mine tunnel intersections are the openings in the tunnel walls where the intersecting tunnels can be entered. Using these cues, no presumptions need to be made about the angle between the intersecting tunnels, thereby enabling robust detection of the junctions. Such an opening is called a **Cross Cut** in mining jargon.

In this paper we propose a new method for detection of openings in walls, based on data from a laser range scanner. The algorithm is a crucial part of the intersection detection of our navigation system. We also present a thorough quantitative evaluation of the algorithm's performance and reliability. In our navigation system the algorithm is accompanied with a corridor detection algorithm [8] to enable high speed reactive[1] navigation based on fuzzy behaviours and a topological map. Recently we have also had access to laser data recorded using a sensor mounted on a LHD. Qualitative experiments show that the performance of the opening detection algorithm on data recorded using a LHD is similar to the results presented in this paper.

## II. INTERSECTION DETECTION

Since none of the methods found in the literature fulfill the requirements of a intersection detection algorithm for use in underground mines, a different method to detect intersections was developed. This method is able to detect the discontinuities in the tunnel walls due to intersecting tunnels far ahead

[1]The term reactive navigation is here referred to as navigation based solely on the sensor readings, with no previous information about the locations of the surrounding walls.

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Fig. 1. LHD vehicle prepared with sensors and control system for autonomous navigation.

of the robot, and is independent of preprocessing of the range data from the laser scanner. Regarding the execution time our feature detection algorithms for junction detection yield an execution time that is only fractions of a millisecond for each scan containing 181 range measurements, well below 0.1 ms on our test system (Intel Pentium M 1.5 GHz, running Linux).

The algorithm to detect cross cuts can be divided in two parts: First, a rough estimation of the direction of the tunnel relative to the robot; Second, detection of cross cuts on each side of the tunnel. The purpose of the cross cut detection algorithm is to provide input for topological localisation and to *anchor* the topological artifacts to enable navigation. Here the term *anchoring* is used to refer to the process of matching an object from the map to an artifact representing a specific perceived feature in the robot environment [9], i.e. to create a connection between the objects in the map and the percepts from the feature detection algorithms. Even though the algorithm is designed to detect cross cuts in mines, it can be used just as well to detect open doors or intersecting corridors in indoor environments [10]. Therefore it will henceforth be referred to as the **Opening** detection algorithm.

The algorithm is based on the fact that the presence of an intersecting corridor will result in a discontinuity in the laser range array, and that such an event therefore can be detected directly in sensor coordinates. By evaluating the difference in range of consecutive laser points all discontinuities of the corridor walls can be detected, at least within a certain range determined mainly by the environment.

Input to the algorithm is the laser data $R$, an array of range measurements, while the only setup parameters are the threshold $\tau$ for minimum width of the openings to detect and the maximum range of the laser $r_{max}$. Output from the opening detection is two sets of openings, one for each side of the robot or tunnel. Pseudo code for the potential opening event detection and two filters for discriminating false positives is displayed in Figure 2.

The first step of the opening detection is to determine which points in the laser data belongs to which wall of the tunnel. If no tunnel information is available, the tunnel direction relative to the robot ($\theta$) is roughly estimated by applying a filter to the laser data $R$. The filter detects directions in

**Algorithm:** findIntersection($R$)
$\theta \leftarrow$findTunnelDirection($R$, $r_\theta$, $N$)
$(R_l, R_r) \leftarrow (R_{0\ldots\theta}, R_{\theta\ldots 180})$
*% Right case*
**for** $n = 0$ to $\theta$ **do**
  **if** $(\|R_n - R_{n+1}\| > \tau \ \wedge \frac{R_{n+1}}{R_n} > 1.3)$ **then**
    **if** $\forall_{x\in 2\ldots\theta}\,[\|R_n - R_{n+x}\| > \tau]$ **then**
      **Find** $\min_{x\in 1\ldots\theta}(\|\text{cart}(R_n) - \text{cart}(R_{n+x})\|)$
      **if** $x \neq 1$ **then**
        **foundOpening** from cart($R_n$) to cart($R_{n+x}$)
  *% Left case analogous*

Fig. 2. The algorithm for detecting intersections, cart($R_i$) gives the cartesian coordinate for $R_i$.

which there are at least ($N$) consecutive laser readings that exceed a specific distance $r_\theta$. Empirical evaluations have shown that using $r_\theta = 3\tau$ and $N$ corresponding to the angle $\alpha = atan(\tau/r_\theta)$ expressed in degrees is a good trade-off between precision and robustness in the estimation. If the filter detects several potential tunnel directions the one that is best aligned with the robots forward direction within a tolerance of $45°$ is selected. The laser range data is then split in right wall and left wall groups with range readings corresponding to angles $0 - \theta$ respectively $\theta - 180$. If on the other hand no potential tunnel directions are found in the forward direction of the robot, the laser data is simply split in two halves corresponding to the left and right side of the robot. However, in order to be able to detect a potential opening that is split with the data, some extra laser points ($N$) in the forward direction are assigned to both the left and right sides.

By evaluating the difference in range of consecutive laser points $(R_n, R_{n+1})$, see Figure 3 and Eq. 1, we have a sufficient condition to locate all potential opening event candidates. The evaluation of the quotient is performed to prevent distant laser readings where the distance between consecutive readings is large from being interpreted as opening events. This initial thresholding locates all potential opening events, but among these we can also get a large number of false positives. For instance will a small hole in the wall that are narrower than the minimum opening width $\tau$ be detected as an opening if the range to the obstacles on the other side of the wall is distant enough, Figure 4 right. Likewise can a cavity in the wall result in two consecutive laser readings that fulfill the threshold requirement of Eq. 1, Figure 4 left. These types of false positives are eliminated in two steps.

$$abs(R_{n+1} - R_n) > \tau \ \& \ \frac{R_{n+1}}{R_n} > 1.3 \tag{1}$$

The first type of false positive opening event is detected by comparing the range value of the first point $R_n$ of the event to all following range readings belonging to the same wall. If the difference in range in any case is shorter than our specified minimum opening width $\tau$ the event can be dismissed.

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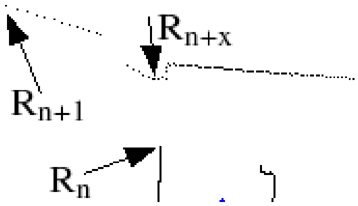


Fig. 3. Detected discontinuity in range scan, robot (small blue triangle) at the bottom looking up. The data is from a T-junction in the University basement.

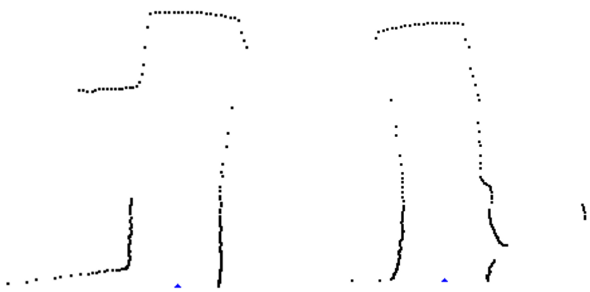

Fig. 4. Two scans from a mine with the robot at the bottom of the images (blue triangles) facing up. The nominal tunnel width is 11 m. **Left:** A scan with one real cross cut to the left and a discrepancy in the right wall that can initially be detected as a potential opening depending on the threshold value $\tau$ Note that $\tau$ can be significantly less than the nominal tunnel width in order to detect narrow side tunnels. **Right**: In this scan there is a small hole in the right wall that will be detected as a potential opening by the threshold function in Eq. 1.

In order to detect the second type of false positive opening events, the laser range measurements have to be transformed into cartesian coordinates. By identifying the laser point $R_{n+x}$ that is closest in Euclidean space to the first point $R_n$ of the event, we have a means of eliminating potential opening events that are likely to be false positives. If the point $R_{n+x}$ is identical to the initial second laser point $R_{n+1}$ of the event (i.e. $x = 1$), the potential opening event can be dismissed since it is likely that the event is not an opening but just a discrepancy in the wall. If not, the two laser points $R_n$ and $R_{n+x}$ unambiguously reveal the presence and location of an intersection.

The output from the opening detection algorithm is the location, the width and the direction of the opening as seen in Figure 5. These parameters are all used later when fusing both perceptions of the same type but at different occasions and different types of perceptions.

## III. Empirical evaluation

The purpose of the opening detection is to identify openings, i.e. holes, in the corridor or tunnel wall as early as possible. In this way the robot can concentrate its perceptual abilities on certain areas that are likely to turn out to be intersections, as well as start preparing for a possible turn. To evaluate the opening detection algorithm two different data sets were recorded in an underground mine. One of these data sets represents an area with extremely high density of cross cuts while the other data set represents an area with no

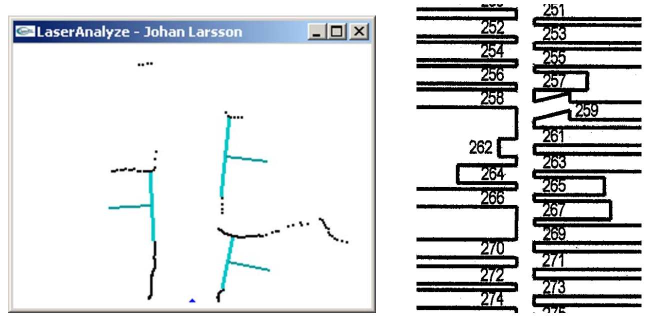


Fig. 5. **Left:** A scan with detected openings. The robot is at the bottom of the image (blue triangle) facing up. Openings are viewed as light blue lines between the detected closer and farther points of the opening. The slightly darker blue line represents the direction of the opening. Three openings are found within the specified maximum range (35 m) **Right:** The same area as shown left, extracted from the map of the mine. The robot is located just above the 261 drift.

ground truth cross cuts at all. These data sets[2] are referred to respectively as the **Gallery** data set and the **Tunnel** data set Each data set consists of a certain number of range arrays, i.e. scans, where each scan represents the distances to the closest obstacles in 181 different directions in a 180° field of view.

Three different test cases were applied to the data sets. All test cases had the same basic parameter, i.e. minimum width $\tau$ of the openings to be detected. The difference was that the test cases have different maximum ranges for the detection of openings. The purpose of this experiment was mainly to get some figures of the success rate of the algorithm, but also to investigate if any systematic classification errors occurred. If such systematic classification errors occur, this information can be used for improving the algorithm.

### *A. Data sets*

The two data sets used in this experiment were recorded in a real mine using a MagellanPro robot equipped with a SICK PLS laser range scanner that has a working area of 180°, i.e. it is capable of measuring the free distance in a half plane in front of the scanner. The used angular resolution was 1°, while the maximum range and range resolution was 50 m and 50 mm respectively. However, even though the maximum detection range of the laser is 50 m, the practical maximum range in the mine is less than 40 m.

To enable recording of data at a velocity comparable to the one of a LHD, the robot was strapped to the roof of a car. The range readings from the laser scanner were then recorded to a file, while the car was driven manually in the mine.

*1) The Tunnel data set:* This data set represents an approximately 200 m long section of almost straight mine tunnel with no intersections, see Figure 6. One example of the 108 scans in the Tunnel data set is displayed in Figure 7.

[2]To allow comparison between algorithms the data sets are publicly available, please contact the authors for further information.

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Fig. 6. Image from the area where the Tunnel data set is recorded.

Fig. 7. An example scan from the Tunnel data set. The laser (triangle) is located at the left of the figure facing right. The distance between scale lines is 10 m. Note that readings of maximum range are not displayed.

*2) The Gallery data set:* The Gallery data set is the "trial by fire" for the opening detection algorithm. Here the walls of the tunnel consist of short wall segments that are often curved and always rough. In between these 5-6 m long wall segments twice as long areas of free space due to cross cuts offer plenty of room for the laser beams to disappear into the darkness, see Figure 8. One example of the 104 scans in the Gallery data set is displayed in Figure 9.

### *B. Experimental setup*

In the evaluation of the opening detection the ground truth was used, i.e. the output from the opening detection algorithm was compared to an existing map of the mine area where the data was recorded. For this comparison a graphical tool was used, Figure 5 left. In the graphical tool one individual scan at a time was evaluated, comparing the detected openings to the corresponding area of the mine map. All occurrences of detected openings were evaluated to determine whether the opening corresponds to a cross cut in the map and were marked as true or false positives. Likewise were the ground truth cross cuts in the map compared to the openings detected by the algorithm to detect true and false negatives.

In the experiment three different maximum ranges for the opening detection algorithm were applied. These were 35 m, 25 m and 15 m, the reason for using different ranges was to evaluate if the success rate and main error types differ depending on the active range. For all test cases the minimum width of the opening was set to 7 m, nominal drift width in the mine is 11 m.

Fig. 8. Image from the area where the Gallery data set is recorded.

Fig. 9. An example scan from the Gallery data set. The laser (triangle) is located at the bottom of the image facing straight up. The distance between scale lines is 10 m. Note that readings of maximum range are not displayed.

The openings are viewed in the graphical tool as a line between the two laser readings corresponding to the opening, see Figure 5. A second line perpendicular to the first line shows the detected direction of the opening. An opening is regarded as true positive if the marked closer side of the opening corresponds to the ground truth of the closer side of the opening in the map within a tolerance of 2 m, Figure 10.

Since each scan can contain more than one opening it makes sense to evaluate the opening detection algorithm's ability to correctly identify the presence and location of individual openings. On the other hand, an evaluation of the algorithm's ability to detect individual openings cannot measure the algorithm's performance in detecting the non-presence of openings in a scan, i.e. classify an entire scan as having no openings. Therefore the evaluation of the algorithm was performed both per opening and per scan.

On the individual opening level there are three relevant classification groups, **TruePositive**, **FalsePositive** and **FalseNegative**. The first corresponds to a ground truth opening that has been detected by the algorithm, the second to the case when the algorithm has detected an opening but there is no ground truth opening. The third case corresponds to a ground truth opening that has not been detected by the algorithm.

When classifying entire scans four relevant classification groups are used, **TrueIntersection**, **FalseIntersection**, **True-**

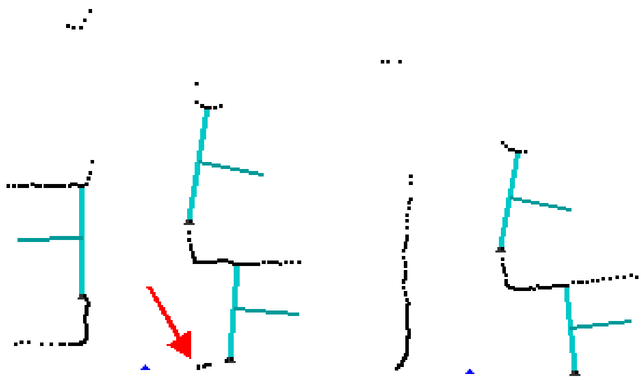

Fig. 10. **Left:** Robot (blue triangle) at the bottom facing up. An opening is detected in the lower right corner corresponding to a side tunnel, but the algorithm locates it too far away from the main tunnel wall. The scan is therefore classified as a false negative since no opening is detected at the true and visible location of the cross cut (red arrow). **Right:** Robot (blue triangle) at the bottom facing up. An opening is detected in the lower right corner where the laser scanner gets a glimpse of the closer wall of the side tunnel. In this case the scan is classified as a false positive.

TABLE I
CLASSIFICATION ON SCAN LEVEL. EACH SCAN CAN CONTAIN MORE THEN ONE OPENING.

| **Scan-wise classification** | | | Detected | |
|---|---|---|---|---|
| | | | Intersection | Tunnel |
| Range 35 m | Ground truth | Intersection | 87 | 10 |
| | | Tunnel | 12 | 103 |
| Range 25 m | Ground truth | Intersection | 96 | 4 |
| | | Tunnel | 4 | 108 |
| Range 15 m | Ground truth | Intersection | 27 | 3 |
| | | Tunnel | 3 | 179 |

**Tunnel** and **FalseTunnel**. TrueIntersection and TrueTunnel corresponds to scans where all ground truth openings have been detected and there are no **FalsePositives**.

The group FalseTunnel and FalseIntersection corresponds to scans where the algorithm has failed to detect at least one ground truth opening respectively reported an opening at a location that does not correspond to a ground truth opening.

### C. *Results*

The Gallery data set consists of 104 scans and the Tunnel data set of 108, this makes in total 212 individual scans that has been classified. All scans have also been evaluated with three different ranges of the opening detection algorithm, 35 m, 25 m and 15 m. The results of the evaluation are displayed as standard confusion matrices both per scan and per feature, although the main analysis of the result is performed feature-wise. Tables I and II display the result per scan respectively per feature. Note that no figures are given for the number of detected "non-openings" in the tables of the feature-wise result since that figure corresponds to the per scan evaluation.

Evaluated on scan basis the success rate of the opening detection algorithm in classifying the 212 scans of the used datasets are 90%, 96% and 97% for an active range of 35 m, 25 m respectively 15 m. Obviously the success rate is higher the shorter the active range of the opening detection

TABLE II
CLASSIFICATION ON THE FEATURE LEVEL.

| **Feature-wise classification** | | | Detected | |
|---|---|---|---|---|
| | | | Opening | No opening |
| Range 35 m | Ground truth | Opening | 251 | 11 |
| | | No opening | 14 | - |
| Range 25 m | Ground truth | Opening | 149 | 4 |
| | | No opening | 5 | - |
| Range 15 m | Ground truth | Opening | 27 | 3 |
| | | No opening | 4 | - |

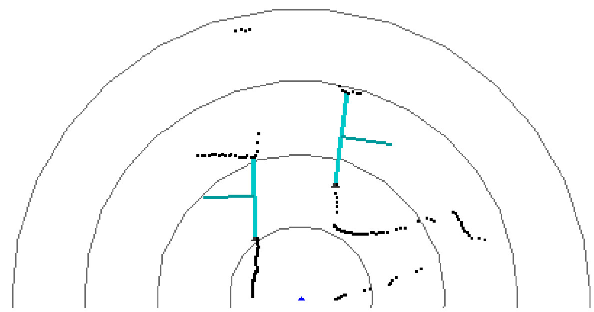

Fig. 11. Example of a scan where the algorithm has failed to detect one opening, due to both of the walls of the side tunnel being visible (lower right). Laser (triangle) at the bottom of the figure facing up, the distance between the scale lines are 10 m.

algorithm is. On the other hand one could argue that the increased success rate is merely a function of less ground truth openings to detect within the active range of the algorithm. In other words, it is easier to correctly classify a scan with no openings than one with openings. This assumption is confirmed when looking at the figures for the success rate on a feature based basis, comparing the number of correctly classified openings to the number of ground truth openings. The success rates for the opening detection algorithm on a feature basis are approximately 96%, 97% and 90% for the active ranges 35 m, 25 m respectively 15 m. When comparing the false positives of the 25 m case to the ones of the 15 m case, it is important to notice that three out of the four false positives of the 25 m case correspond to the three false positives in the 15 m case. This means that out of the extra 123 (153-30) ground truth openings in the range 15–25 m in the 25 m case, the algorithm only fails to detect one. Likewise does the increased range from 15 to 25 m only contribute with one (5-4) false positive. These figures indicate that the algorithm is better suited for classifying openings located farther away than those close to the laser scanner.

When clustering the different error cases three main types occur.

1) Detecting a false opening due to stray laser measurements, i.e. between two valid readings in a scan, one or more erroneous readings at maximum range occur, Figure 12. This error is typically found on large distances where the angle between the surface to measure the distance to and the laser beam is very small, in other words when the laser beam is more or less parallel to the measured surface.

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Fig. 12. Example of a scan where the algorithm has falsely detected an opening. The stray range reading causing the false detection is indicated by the arrow. Laser (triangle) to the left of the figure facing right, the distance between the scale lines are 10 m.

2) When both walls of a side tunnel are visible to the laser, Figures 10 and 11. This case is often the source to a **FalsePositive** and a **FalseNegative** pair, Figure 10 left. In other words, that the opening to the side tunnel is not detected near the wall of the main tunnel as intended, but laterally offset in the direction of the side tunnel. This type of error occur when the distance to the side tunnel is short and the cross cut has already been correctly detected in several previous scans while approaching the intersection.
3) Failure to detect an opening far ahead but within the active range of the algorithm. In some cases this error occur when only one or two individual range values correspond to the farther wall of the opening that the algorithm fail to detect. This is a case where it would be almost impossible even for a human looking at the laser data to detect that there is an opening, simply because the laser data do not contain enough information. In other cases it is the shape of the wall and corner of the further wall of the side tunnel that causes the algorithm to fail to detect the opening. Four of the openings that the algorithm fails to detect have more than three laser range values corresponding to the further wall of the side tunnel, and it is no difficulty for a human looking at the data to detect that there is an opening.

To eliminate the false positives introduced by the first error type would be simple by just adding the criteria that laser readings of maximum range should be disregarded. By this the lion share of the false positives that occur in the data sets of the experiments would be eliminated (8 out of 14 for the 35 m test case).

The second error type could be avoided if laser readings close to the machine, or laser readings that have an angle to the forward direction that exceeds a certain value were dismissed from the evaluation. However, this would greatly reduce the ability of the algorithm to detect openings when the laser is not aligned to the tunnel direction.

The third error type is probably something that one has to accept. In order to avoid false positives the algorithm requires that some conditions regarding the range measurements are fulfilled, see Section II. It has to be evaluated further if some more condition can be used in disjunction with the currently used to increase the algorithms sensibility to detect true openings without increasing the number of false positives.

## IV. CONCLUSIONS

In this paper we have proposed a new algorithm to be used for intersection recognition in underground mines. The thorough empirical evaluation shows that the algorithm is robust and able to reliably detect and determine the location of the openings in the tunnel walls due to intersecting tunnels. The results also suggest a few changes to the algorithm that could improve its performance even further. One of the main features of the algorithm is its efficient computation, which enables it to be implemented on small embedded processors, even though it performs well on data from real mine environments. Another advantage is the simplicity, the algorithm only needs two parameters as input and can easily and intuitively be tuned for different environments. In other experiments [10] the algorithm has proven to be flexible and easy to adapt to as different environments as mine tunnels and office corridors. While the algorithm already has been used for autonomous reactive navigation, the next step is to explore the possibilities to enhance semi autonomous teleoperation of mobile robots and in particular LHD vehicles in underground mines.


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