

USING PASSAGES TO SUPPORT OFF-ROAD ROBOT NAVIGATION

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Abstract: In this paper an approach for the detection of passages and their use in autonomous off-road robot navigation is presented. The authors argue that many two-layered architectures of robot navigation systems suffer from the gap between the typically coarse-grained high-level path-planning and the basically reactive low-level collision avoidance. In this context, passages shall be defined as paths leading through obstacles. The proposed approach is based on the idea that passages in the proximity to the robot should be evaluated with respect to their relevance for reaching the target area in order to avoid local detours by following suitable passages. The detection and assessment of passages is based on virtual sensors, a standardized data representation offering a unified, straightforward, and flexible retrieval mechanism for accessing the data provided by different sensor systems. For the evaluation of passages the authors introduce the concept of virtual sensor probes which can move independently from the robot. That way the point of view on the environment information can be tailored to support the detection and evaluation strategy. The proposed approach was deployed on the mobile off-road platform RAVON which serves as a testbed for the experiments carried out in the context of this work.

1 INTRODUCTION

Many robot navigation systems are designed following a two-layer concept: A deliberative path-planner, the “navigator”, builds global maps, which it uses for high-level path planning. The output of this planner are single path points, which are passed to a lower level component, the “pilot”. This component transforms the target coordinates into motion commands, taking into account sensor data to realize collision avoidance. The pilot typically operates in a nearly reactive way, storing only little state information and having a very much limited view on the robot’s environment. In such an architecture, the pilot exerts a draw towards the target, which the anti-collision system may counteract, resulting in the robot driving around obstacles towards the target.

While this principle works well in simple environments, it can easily fail in more complex terrain. As the collision-avoidance works locally, missing the “big picture”, it cannot keep the navigator from drawing the robot away from a path and into small openings between obstacles, which are so wide

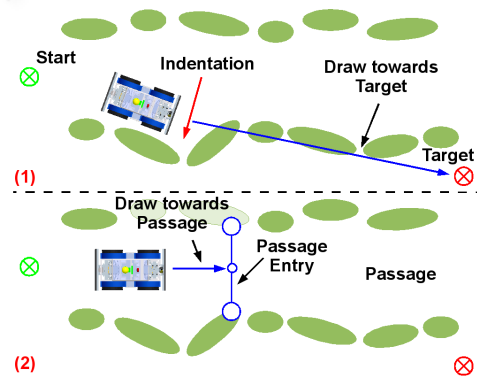


Figure 1: The problem of dealing with indentations.

that the collision avoidance does not get active directly, but which could be easily recognized as indentations when using a larger scope (see Figure 1, (1)).

The idea that is presented here is to search for paths leading through obstacles, so-called *passages*, and to evaluate them with respect to their value for the robot’s navigation. In the described situation, the path the robot is driving on would be detected as such a

passage, while the indentation would be ignored (see Figure 1, (2)). Furthermore, estimating a passage's orientation would allow for directing the robot in a way that it can more easily enter the passage.

It shall be emphasized here that the described approach targets at environments in which there is no clear path that could be followed using a path tracking approach like the ones mentioned in section 2. Instead, the paths constituted by passages are consecutive spaces between obstacles that are wide enough to be used by a robot.

2 STATE OF THE ART

The concept of separating a robot navigation system into two layers is widespread and described in many places in the literature. The classic separation results in a low-level system for local navigation that has a limited view on the world and operates in a fast, yet shortsighted manner. Different approaches have been followed to establish the interaction of the two parts ((Wooden et al., 2007), (Ranganathan and Koenig, 2003)). An approach for detecting narrow passages in indoor environments is described in (Schröter, 2005). Its author used the polar data of a laser scanner to identify and assess passages and combined it with 3D rectangular objects reconstructed from the images of a stereo vision system to identify doors. The algorithm used for processing the laser data resembles the one presented here. However, it only processes the data of one polar sensor and not of several (virtual) sensors. Evidently, using a stereo system in such a way to detect passages will not work in unstructured off-road environments. Approaches for keeping the robot from leaving the road or path include detecting curbs using a light-stripe scanner (Thorpe et al., 2003), detecting lanes using edge extraction from images, or road detection using a combination of LADAR data and color information (Hong et al., 2002). The work described in (Lieb et al., 2005) uses the assumption that the vehicle is situated on the road to form templates of the road's appearance and from them and current images calculates an estimate of the road's curvature. (Alon et al., 2006) describes a system that uses two different path-finding algorithms in parallel and uses the output of the one with the highest confidence. However, all of these approaches are tailored to detecting a path in an environment that is completely different from the one of this work.

3 SYSTEM ARCHITECTURE

3.1 A Two-layered Navigation System

The work at hand is embedded into a two-layered robot navigation system consisting of a classical deliberative navigator (Braun and Berns, 2008) on top of a behavior-based system for local navigation, i.e. target-oriented motion and collision avoidance (Schäfer et al., 2008b). The navigator creates and updates topological maps of the environment, which are used as basis for the path planning process. It sends the points of a path one by one to the lower layer, from which it receives basic status information.

3.2 Virtual Sensors

Special behaviors of the local navigation system translate the goal poses into motion commands, which are altered by a behaviour-based anti-collision system. The behaviors use a special type of representation that provides a powerful yet slim interface to arbitrary types of sensors. Different aspects and ranges of the robot's environment are abstracted using polar and Cartesian sector maps, which represent *virtual sensors* (VS). Polar maps are defined by start and stop angles whereas Cartesian maps have an extent in positive and negative y-direction. Each sector holds the most relevant representative of the area it covers. In the architecture presented here, the VS are filled with data from a scrollable, robot-local, and orientation-fixed grid map that stores highly preprocessed sensor data of a pannable laser range finder (Schäfer et al., 2008a). Using this short-range map as input for the virtual sensors allows for monitoring areas which are currently not in the range of the robot's real sensors.

3.3 Virtual Sensor Probes

While the virtual sensors used for collision avoidance are defined with respect to the robot coordinate system (RCS) and are fixedly mounted on the robot, virtual sensors that are used to gather information about specific structures in the environment have to be fix with respect to the working coordinate system (WCS). Hence their pose in terms of the RCS changes whenever the robot moves. This special type of virtual sensor is called *virtual sensor probe* (VSP).

The preprocessing of the sensor data, the coordinate transformations (sensor to robot to working CS), and the filling of the VSPs with the correct data is done in the sensor processing subsystem. Therefore higher components do not have to deal with these technical details, but can simply provide a WCS pose

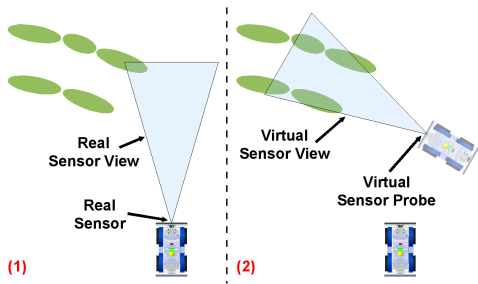


Figure 2: The views of a real sensor and a virtual sensor probe.

for a VSP and be assured that it is filled with the correct information.

Using VSPs, the robot can “look” at a place in the environment from a different point of view (see Figure 2). While this naturally does not yield new information that the robot cannot gather from its actual pose, it structures the existing sensor data in an abstract way, allowing for the use of more straightforward algorithms.

4 THE USE OF PASSAGES

4.1 Passage Detection

A passage is defined by its entry, which is delimited by an obstacle on each side. These two obstacles are called *Passage Entry Points* (PEP), the line connecting them *Passage Entry Line* (PEL). The algorithm for detecting passages traverses all sectors s_i of a polar sector map (see Figure 3, (1)) covering the area in front of the robot and compares the distances d_i of the obstacles o_i (with $0 \leq i < n$ and n being the number of sectors).

If o_{j+1} is farther away from the origin than o_j by at least the threshold t_0 , then o_j is considered as potential first PEP. Be o_k with $k \geq j+1$ the first obstacle that is closer to the origin than o_{j+1} by at least the threshold t_1 . Then o_k is the second PEP and all obstacles between o_j and o_k are considered to lie within the passage. The new passage is added to a list and the search goes on with the remaining sectors. In the following, pseudocode for the detection algorithm is shown.

For every passage, the *passage entry midpoint* (PEMP), which is defined as the point lying in the middle between o_j and o_k , is calculated. It is a passage’s characteristic point and, as described below, is important for navigating into a passage.

As the distance values in the sectors refer to the virtual sensor’s coordinate system, the algorithm

Algorithm 1. Detecting Passages.

```

searching_for = cFIRST_PEP; // the status of the search process
index_first_peg = 0; // the first PEP's index
index_point_in_passage = 0; // the index of a point within the passage
for (i = 0; i < n - 1; i++) do
    if (searching_for = cFIRST_PEP) then
        if (d[i] - d[index_first_peg] < t.0) then
            index_first_peg = i;
        else
            searching_for = cSECOND_PEP; index_point_in_passage = i;
    else // currently searching for second PEP
        if (d[index_point_in_passage] - d[i] >= t.1) then
            passages.add(new Passage(o[index_first_peg], o[i]));
            index_first_peg = i;
            searching_for = cFIRST_PEP;
        else
            // nothing to be done here
    
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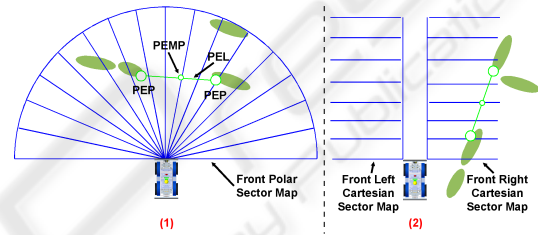


Figure 3: The sector maps used for passage detection.

tends to not detect passages that lie in the sideway parts of the polar sector map. To overcome this deficiency, two Cartesian sector maps are also used as data sources (see Figure 3, (2)). Due to the generic interface of the sector maps, the algorithm described above needs only simple modifications to process the data of Cartesian sector maps.

It shall be remarked here that by using sector maps, the passage detection and evaluation algorithms do not have to access the complex grid map, but can operate on a much simpler data structure.

A temporal aspect was integrated by creating and updating a list of *persistent* passages: In every sensor processing cycle, the PEMP of each passage that is detected is compared to the PEMP of each persistent passage. Two passages are regarded as similar if the distance between their PEMPs is below a certain threshold. Taking into account the passages’ PEPs was also considered, but experiments showed that the distance between two PEMPs is a suitable criterion for similarity. If a similar persistent passage is found, it is updated with the newly found passage, i.e. the persistent passage’s PEPs and PEMP are set to the ones of the new passage. If not, the newly found passage is added to the list of persistent passage. Persistent passages that have not been seen for a certain amount of time are removed.

4.2 Passage Evaluation

The passage evaluation operates on the persistent passages. Its first step checks whether a passage fulfills the *basic requirements*, i.e. whether it is wide enough, has a minimum age, lies in a suitable direction, has a suitable orientation, and is long enough. A passage which fulfills these requirements is called *suitable passage*.

The first four aspects can be checked easily. A passage's width is calculated as the distance between its two PEPs. If a passage's entry is too narrow for the robot, it is obviously irrelevant for navigation. The age is calculated as time that has passed between the first and the latest detection. Passages which have not been seen for a minimum amount of time are ignored.

As passages shall be used to assist the navigation system in driving the robot to its target, a suitable passage shall lie in the direction of the target with respect to the robot. This is checked by comparing the orientation of two lines—one going from the robot to the target and one going from the robot to the PEMP. Furthermore, a suitable passage has to point approximately in the direction of the target. This is checked by first calculating the orientation of a line that starts at the PEMP and is perpendicular to the PEL. This orientation is then compared to the one of a line starting at the PEMP and going to the target. If the difference between the two orientations is below a certain threshold, the passage is considered to be well-oriented.

A VSP represented by a Cartesian sector map consisting of only one sector is used to "look" into the passage, measure the distance to the closest obstacle and thus estimate the passage's length (see Figure 4, (1)). Using a sector map as VSP instead of accessing the grid map directly facilitates the data access and spares the evaluation component more complex data processing.

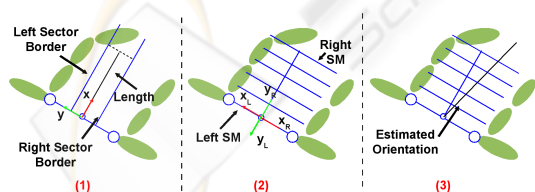


Figure 4: The sector maps for length and orientation estimation.

It is advisable to navigate the robot in a way that it reaches the PEMP with approximately the passage's orientation as this facilitates entering the passage. The orientation estimation described above does not take into account information about the presence of obstacles in the passage. Thus a more precise estimate is

calculated for the passage that best satisfies the above criteria, the *relevant passage*. Two Cartesian sector maps are used to monitor the sides of the passage (see Figure 4, (2)). Each of their sectors stores information about the closest obstacle in the area it covers, i.e. it contains a local estimate of how far away the passage's border is. For each sector, the angle between the following two lines is calculated: (a) a line that starts at the PEMP, is perpendicular to the PEL and points into the passage, and (b) a line going from the PEMP to the sector's obstacle. The passage's orientation is calculated from the arithmetic mean of these angles, so its axis is pushed away from obstacles (see Figure 4, (3)). Of course this is only a rough estimate, but it can be calculated using the existing mechanisms, while other methods need more complex, specialized algorithms.

4.3 Integration

The component that detects and evaluates passages and navigates the robot to a PEMP has been implemented as behavior and integrated into the behavior-based system mentioned above. It is referred to as *passage behavior*. Whenever it detects a relevant passage, it gets active and sends the coordinates of the PEMP to the behaviors that drive the robot to given target coordinates. These behaviors are also used by the navigator, but when a passage is detected, the behavior gets active and overwrites the target pose provided by the navigator.

In some cases, an inhibition of the passage behavior is sensible. If the robot follows a wide path that leads to the target and has only few obstacles, the passage behavior would constantly detect a relevant passage and would try to guide the robot to its PEMP. If the number of visible obstacles is too low, the orientation calculations would produce poor estimates. Using these passages would result in a swinging robot motion although it would be possible to drive straight ahead. To cope with this problem, another behavior uses a wide Cartesian sector map to monitor the area in the direction of the target. If there is no obstacle, there is no need for using passages, so the monitoring behavior inhibits the passage behavior and thus returns control to the navigator.

The system's operation shall be illustrated taking up the example from section 1. At first, only a small part of the situation is visible to the robot (see Figure 5, (1)). A large passage is detected between the outer obstacles. The area in the direction of the target (green square) is free, so the passage is ignored. As soon as the free space to the right of the robot is recognized as indentation, the navigation system guides

the robot towards the newly detected suitable passage instead of driving into the indentation (see Figures 5, (2) and (3)).

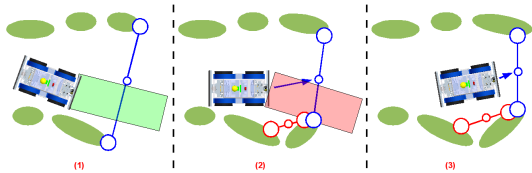


Figure 5: The operation of the passage behavior in the situation depicted in Figure 1.

5 EXPERIMENT AND RESULTS

For experiments the passage detection mechanism presented in this paper was integrated into the navigation software of the mobile off-road platform RAVON¹, a 4WD vehicle with the dimensions and weight of a city car, which is equipped with a variety of sensor systems (e.g. 2D laser scanners, a 3D laser scanner, stereo camera systems). Detailed information about the robot can be found in (Armbrust et al., 2009).

Several test runs have been conducted in the Palatinate forest, of which one shall be presented here as example². RAVON started on a trail and was given a target location several hundred meters away. Its task was to drive there fully autonomously. Figure 7 shows a part of the run as pose trace. Red crosses symbolize obstacles that were classified by the sensor processing system as definitely not traversable. Vegetation that was probably traversable when driving cautiously is marked with green crosses. It shall be pointed out here that the robot drove the complete route depicted in the figure without any user action.



Figure 6: RAVON.

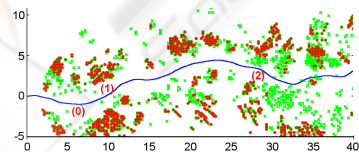


Figure 7: The pose trace with the checkpoints. The unit of length is meter.

Different passages were detected during the drive. For lack of space, only three significant checkpoints

¹Ravon: Robust Autonomous Vehicle for Off-road Navigation

²video showing large part of test available at: <http://rrrlab.cs.uni-kl.de/robot-gallery/ravon/>

shall serve as examples here. For each of them, a visualization of the scrollable grid map filled with the 3D scanner’s data is depicted (see Figure 8). The robot is situated in the map’s center (blue square). The colored circles depict various types of obstacles (red: too high to be driven over; green: other types of obstacles with ground contact; pink: places where the robot could hit the ground). The direction to the target is visualized by a red line starting at the robot’s center. Passages are visualized with circles for the PEPs and PEMP, and lines for the PEL and for visualizing the first and second orientation estimates. For reasons of clarity, only two types of passages are displayed: suitable, but not relevant ones (green), and relevant ones (blue).

Shortly after the start, at checkpoint 0, the path made a slight turn to the left. The relevant passage was oriented to the left, following the path (see Figure 8, (0)). Although it did not lie exactly in the direction of the target and was oriented a bit away from it, it was still suitable. While this was a good first example of the passage behavior’s operation, the combined action of the navigator and the anti-collision system would most likely have dragged the robot around the obstacles to its right.

At checkpoint 1 (see Figure 8, (1)), the deviation of the path’s direction from the direction to the target was so large that following the navigator’s drag would have led the robot into the underwood. The usage of the passage along with its orientation resulted in the robot driving a curve around the obstacles to its right.

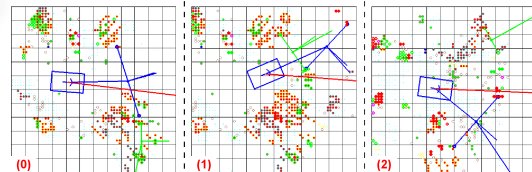


Figure 8: The situation at the three checkpoints.

At the last checkpoint (see Figure 8, (2)), the robot’s motion would have probably been the following without the use of the passage: When driving towards the target, the robot would have gotten so close to the obstacles ahead of it that the collision avoidance behaviors would have had to turn it to the left or the right. Due to noisy sensor data and the lack of a larger scope, it is possible that the robot would have been turned to the left, thus driving straight into the underwood. At this point, backing off maneuvers would have to be conducted. By contrast, the detection of a suitable passage made the robot turn to the right. It avoided the obstacles before getting too close to them and stayed on the trail. Due to the obstacles

on the left border of the trail, no suitable passage was detected there—which is the desired behavior of the detection component.

6 CONCLUSIONS AND FUTURE WORKS

In this paper a concept for passage detection tailored to navigation in terrain with many obstacles and without a clear path was presented. Furthermore, a loosely coupled interaction of the passage detection facility with a topological navigator on the basis of passage orientation estimation was proposed. A suitable passage is negotiated by continuously passing the characteristic passage entry midpoint to a behavior-based point approacher. That way non-holonomic platforms—as presented in the experiments by example of the off-road robot RAVON—can enter even narrow passages without unneeded maneuvering.

The presented system is capable of leading the robot through complex terrain on the basis of a single target location avoiding local detours where possible. As only local terrain information is available on this layer, difficulties like dead ends still remain a problem. As a next step, the passage behavior shall provide detected passages to the navigator, which shall store them in terms of navigation-relevant spots. When a dead end is reached, the navigator shall tag passages leading to the current location as dead end entry points to avoid global detours in the future.

Furthermore, the system shall be extended so that other types of navigation-relevant places like very narrow ways (which require especially careful movements) or crossroads (which offer several options for the robot to proceed to the target area) are also detected. Exchanging information about these places with the higher navigation layer will support backtracking if following a path turns out to be unhelpful in getting to the target.

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REFERENCES

- Alon, Y., Ferencz, A., and Shashua, A. (2006). Off-road path following using region classification and geometric projection constraints. In *Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, volume 1, pages 689–696, New York, NY, USA. IEEE Computer Society (Washington, DC, USA).
- Armbrust, C., Braun, T., Föhst, T., Proetzsch, M., Renner, A., Schäfer, B., and Berns, K. (2009). Ravon — the robust autonomous vehicle for off-road navigation. In *Proceedings of the IARP International Workshop on Robotics for Risky Interventions and Environmental Surveillance 2009 (RISE 2009)*, Brussels, Belgium. IARP.
- Braun, T. and Berns, K. (2008). Topological edge cost estimation through spatio-temporal integration of low-level behaviour assessments. In *Proceedings of the 10th International Conference on Intelligent Autonomous Systems (IAS-10)*, Baden Baden, Germany.
- Hong, T.-H., Rasmussen, C., Chang, T., and Shneier, M. (2002). Road detection and tracking for autonomous mobile robots. In *Proceedings of SPIE Aerosense Conference*, Orlando, FL, USA.
- Lieb, D., Lookingbill, A., and Thrun, S. (2005). Adaptive road following using self-supervised learning and reverse optical flow. In *Robotics: Science and Systems*, pages 273–280, Cambridge, Massachusetts, USA.
- Ranganathan, A. and Koenig, S. (2003). A reactive robot architecture with planning on demand. In *Proceedings of the 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1462–1468, Las Vegas, Nevada, USA.
- Schäfer, H., Hach, A., Proetzsch, M., and Berns, K. (2008a). 3d obstacle detection and avoidance in vegetated off-road terrain. In *IEEE International Conference on Robotics and Automation (ICRA)*, pages 923–928, Pasadena, USA.
- Schäfer, H., Proetzsch, M., and Berns, K. (2008b). Action/perception-oriented robot software design: An application in off-road terrain. In *IEEE 10th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, Hanoi, Vietnam.
- Schröter, D. (2005). *Region & Gateway Mapping: Acquiring Structured and Object-Oriented Representations of Indoor Environments*. PhD thesis, Institut für Informatik der Technischen Universität München, München, Germany.
- Thorpe, C., Carlson, J., Duggins, D., Gowdy, J., MacLachlan, R., Mertz, C., Suppe, A., and Wang, B. (2003). Safe robot driving in cluttered environments. In *11th International Symposium of Robotics Research*, Siena, Italy.
- Wooden, D., Powers, M., MacKenzie, D., Balch, T., and Egerstedt, M. (2007). Control-driven mapping and planning. In *Proceedings of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3056–3061, San Diego, CA, USA.