Navigation and Routemark-Detection of the Bremen Autonomous Wheelchair

Thomas Röfer and Rolf Müller*

Bremer Institut für Sichere Systeme, TZI, FB3, Universität Bremen, Postfach 330440, 28334 Bremen, Germany

Abstract. This paper introduces the concept of a psychologically inspired navigation approach for an autonomous wheelchair. It presents the implementation of the architecture's basic modules and discusses the higher levels of the control-system that are still under development. The recognition of routemarks is of crucial importance in this architecture. An approach for employing 3-D structures of the environment for this purpose is proposed.

Key Words. Robotics, Wheelchair, 3-D Vision, Structure from Motion, Route Navigation

1 Introduction

The representation of spatial knowledge is a research topic in many scientific fields, e.g. in biology, psychology and robotics. In Germany, the Deutsche Forschungsgemeinschaft supports the priority program "Spatial Cognition" that facilitates inter-disciplinary collaboration on this subject. The authors' group is in this priority program and is doing research in the detection of landmarks and routemarks and their use for the navigation of an autonomous mobile system—the Bremen Autonomous Wheelchair. The architecture of the system follows certain models that have been discussed with the psychological working groups in the priority program (Krieg-Brückner *et al.*, 1998).

2 The Bremen Autonomous Wheelchair

A wheelchair is used as an experimental robot platform in Bremen. It has four wheels. The front axle drives the wheelchair while the back axle is used for steering. Therefore, the wheelchair moves like a car driving backwards. It is equipped with a computer and several sensors. The sensors are assigned to three control subsystems (cf. figure 1):

Collision Detection. The wheelchair uses its bumpers, infrared sensors, and wide-angle ultrasonic sensors to detect collisions with the environment.

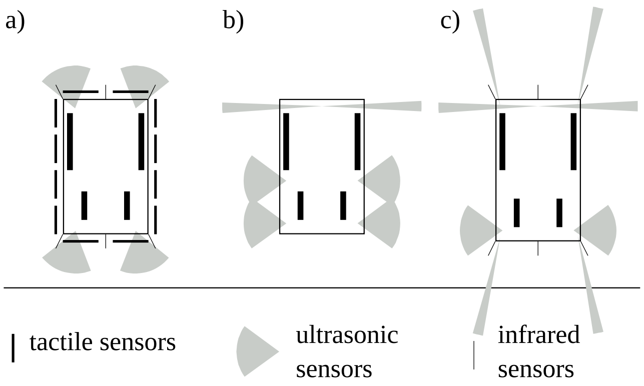


Figure 1 *The sensor control subsystems. a) Collision detection. b) Steering restriction. c) Navigation.*

As long as an obstacle is perceived by the infrared and ultrasonic sensors, respectively, the wheelchair is able to stop before physical contact is made.

Steering Restriction. As the wheelchair is steering with its back wheels, its rear swings out very heavily. To prevent it from colliding with obstacles on the side during driving maneuvers, the distance to the closest obstacle is measured and the steering angle is reduced as much as necessary to avoid a collision.

Navigation. Six narrow-angle ultrasonic sensors and six infrared sensors are employed for navigation purposes. They have been chosen because their measurements do not only reflect a certain distance to an obstacle but also determine it in a definite direction. However, two wide-angle sensors to the side support the navigation subsystem at the moment.

The readings of the sensors are recorded in an obstacle map (cf. figure 2b). This map plots the local environment around the wheelchair and represents an area of 4×4 m^2. When the wheelchair drives on, the measurements in the map are shifted in the same way as the environment passes along the moving wheelchair. Everything that is scrolled out of the map is forgotten, as are measurements that are older than 30 seconds. This allows the wheelchair to cope with dynamic obstacles. Thus the local obstacle map corresponds to a short term memory. The map is only used for local navigation maneuvers. Hence, the measurements are simply stored in the map and no probabilistic sensor model is used.

The information in the obstacle map is abstracted by four *virtual sensors* in the map; their measurements are used for navigation. The virtual sensors

a) 

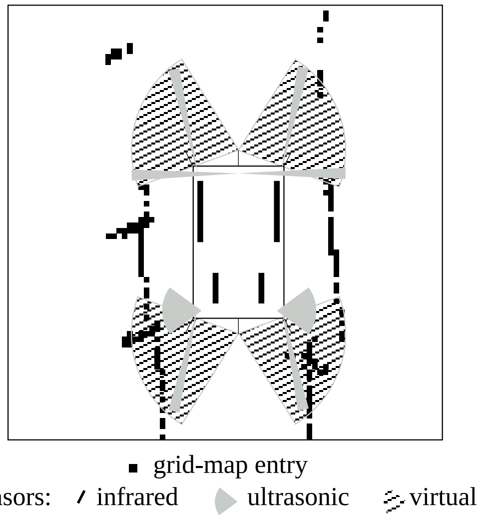
b) 

Figure 2 *a) The Bremen Autonomous Wheelchair b) Local obstacle map.*

work like ultrasonic sensors: they determine the distance to the closest obstacle in their measuring range. In contrast to real sensors, the virtual ones only measure distances to objects already represented in the obstacle map. Thus, they can exploit the sensory data that has been collected in the past 30 seconds; they may even detect an obstacle that the real sensors currently overlook. Two virtual sensors scan the map from a position that, in reality, is 10 cm in front of the wheelchair; the other two scan the map 10 cm behind the vehicle. In each pair, one is oriented towards the left side; the other towards the right side (cf. figure 2).

3 Basic Behaviors

Several basic behaviors, e.g., wall-following and turning-into-door, form the basis of the presented navigation method. They enable the wheelchair to move in corridors, and to enter and exit rooms. They are fairly robust against changes in the environment because they hardly ever assume fixed compositions of the surroundings. Their implementation is based on the aforementioned virtual sensors. Six basic behaviors have been implemented:

Center between Walls. If this behavior is selected, the wheelchair will try to measure the same distance with both of the front virtual sensors. To achieve this, it always steers in the direction of the larger measurement. While performing this behavior, the wheelchair is driving forwards. As it is possible that an obstacle may have been overlooked, the collision detection subsystem perceives it and stops the wheelchair. In this case, the wheelchair performs the same behavior in backward direction for a distance of 50 cm and then returns to driving forwards. Normally, the infrared sensors have detected the missed obstacle during the collision. As their measurements have been recorded in the obstacle map, the wheelchair is aware of this obstacle during further actions. To perform the same behavior while driving backwards, the difference between the two virtual sensor readings simply has to be inverted.

Follow Left/Right Wall. Wall-following is realized by a slightly modified wall-centering behavior. The only difference is that the measurements of the virtual sensor that is opposite to the wall are limited to a maximum distance. Therefore, the wheelchair assumes that there is another wall within this distance and centers itself between this virtual wall on one side and the real one on the other side. If the real corridor is narrower than this virtual one, there is no change to the wall-centering behavior.

Turn into Left/Right Door. These two behaviors enable the wheelchair to turn into a door that is either in the left or the right wall. They are quite similar to the wall-following behaviors. The only difference is that on the side of the door, no virtual sensor is used. Instead, the measurement of the real narrow-angle ultrasonic sensor is used that is oriented toward this side. In this way, the hole between the door-jambs can be determined as soon as possible. If the wheelchair has turned more than 60°, it automatically switches to the wall-centering behavior.

Stop. As it is always the goal of the wheelchair to reach a certain position, it has to stop when it has arrived at the target position.

4 Semi-Local 3-D Marks

The basic behaviors enable the wheelchair to *move* in an office environment. In order to also allow it to *navigate*, it must be able to localize itself in the environment. Therefore, it has to be capable of recognizing reference points in the surroundings, e.g. to switch to the next behavior. In the navigation approach that is presented in this paper, these reference points are called *routemarks* because they are used to localize the wheelchair's position along a certain route.

Currently, only artificial 2D-marks are employed, determined by an image processing algorithm. However, the long-term goal of the authors' research group is to use some features of the environment's 3-D structure as routemarks. To this end, it is desirable that the system can use local structures typically present in its surrounding as natural routemarks or landmarks.

Such natural landmarks or routemarks should be recognized in a robust manner, independent of orientation, illumination, or surface variations in dynamic environments. It is intended to use significant 3-D structures such as corners, doors or boxes. The visual estimation of depth in a small (semi-local) image region is a fundamental prerequisite for the detection of such semi-local 3-D marks. The visual estimation of depth is usually based on at least two images. These are either taken simultaneously in stereo vision (Dhond and Aggarwal, 1989) or subsequently in so-called "structure from motion" approaches (Aggarwal and Nandhakumar, 1988). Here, the second approach is used because utilizing a single camera is cheaper and takes less calibration effort, and structure from motion is computationally very efficient and thus advantageous for real time applications.

The approach consists of two major steps: the estimation of the *focus of expansion* which is the intersection of the heading direction vector and the image plane, and the subsequent estimation of *depth*. The focus of expansion is estimated by a method that was developed in the authors' group. It was described in detail by Herwig (1996). From two consecutive camera images, the intensity derivatives with respect to time t and spatial coordinates x and y are estimated. Assuming short-time constancy of brightness of a point in the observed scene, the normal optical flow field is estimated from those derivatives. The focus of expansion is estimated from the normal optical flow field by minimizing a cost function. This method has been shown to be robust with respect to observed scenes and noise, moreover it is computationally efficient and has been used in real time robotics applications.

In the second step, the ratio of local image depth to the observer's speed is estimated from the normal optical flow field and from the position of the focus of expansion, as Herwig (1996) proposed.

5 Route Navigation

In the second layer of the control hierarchy, the basic behaviors and the routemark recognition are combined. On this tactical level, the environment is represented as a set of routes. A route is a static way from a starting location to a target location. The wheelchair can drive along such a route by a concatenation of different basic behaviors while routemarks are used to trigger the starting and changing of these behaviors. They are the reference marks along the route. Therefore, a route is represented as a sequence of basic behaviors and the routemarks that trigger these behaviors. This sequence can be learned by the wheelchair, e.g. when a teacher controls the vehicle along the route by switching between the available behaviors (cf. figure 3). Meanwhile, the camera scans the surroundings for routemarks and inserts them into the *routemark map*. When the teacher alters the wheelchair's behavior, it stores the view of the routemark map as the trigger for the new operation.

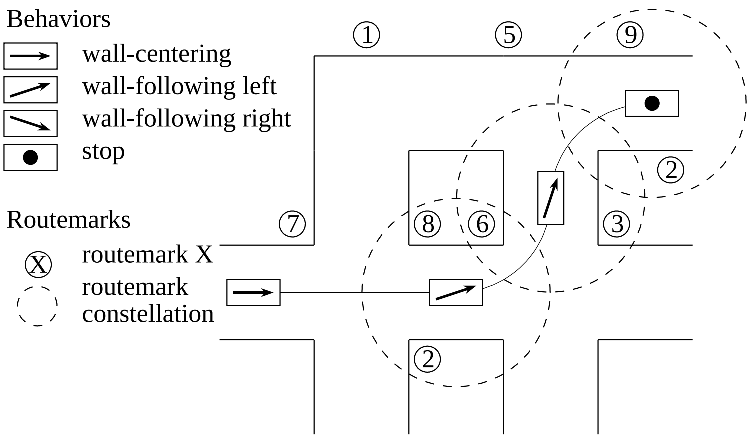


Figure 3 *Teaching of routes.*

Routemark Map. As the sizes of the artificial routemarks are known, the distances to them—as it will be the case for the semi-local 3-D marks—can be determined. Therefore, the position of a mark relative to the wheelchair can be calculated from its distance and its bearing. This allows the creation of another map: the routemark map. This map is similar to the obstacle map that has already been presented. When the wheelchair moves, the positions of the marks in the map are adjusted on the basis of the vehicle's dead reckoning system. Similarly to the obstacle map, the routemark map is local to the wheelchair, i.e. it only maps a region of a radius of 5 m around the vehicle. All routemarks that move out of this radius are forgotten. Through the routemark map, the wheelchair knows the positions of all marks in its vicinity, even if its camera does not currently see them. Hence, it represents a *view*, i.e. the current routemark constellation of a certain place.

Multiple Routemarks. When the wheelchair drives along the learned route autonomously, it executes each recorded behavior until it recognizes a part of the routemark constellation that it has stored during the training to trigger the change to the next behavior. As it cannot be assumed that the wheelchair reaches exactly the same positions during the training and the autonomous repetition, it cannot compare the stored routemark constellation with the current one directly. Instead, the intersection of the stored routemark constellation and the current state of the routemark map is used. If at least one common routemark is found, it is checked whether the wheelchair has passed all these common routemarks. It has "passed" a routemark if the current bearing of a mark is further back than the bearing

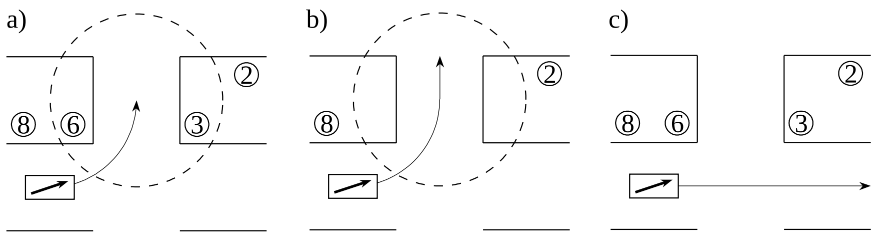


Figure 4 *Possible errors. a) Learned route segment. b) All routemarks missing. c) Erroneous carrying out of behavior.*

of the stored mark. As soon as all common routemarks have been passed, the wheelchair switches to the next behavior of the route. This solution is robust against the absence of single marks, but it tries to reproduce the moment of switching the behaviors as precisely as possible by using multiple marks.

As a single recognized routemark is sufficient for switching from one behavior to the next, behaviors might be switched too early if all routemarks of a certain place are stored because it is possible that the same marks have already been present earlier in this route segment. Since the decision when to switch to the next behavior is based on the bearings of the marks, it is necessary to use only those marks that have their furthest back bearing at the end of the route segment.

Errors. In spite of the use of multiple routemarks for the switching of behaviors, errors during the autonomous drive of the wheelchair cannot be ruled out. Two types of errors are possible (cf. figure 4):

1. All routemarks for switching a behavior have been missed. This can happen, e.g. if routemarks are hidden by persons (cf. figure 4b).
2. A behavior is performed differently than during the training. If, e.g., the wheelchair should follow the left wall and misses a turn-off because a person blocks the passage, the vehicle drives straight on where it should have turned left (cf. figure 4c).

In both cases, two possibilities exist to terminate the erroneous behavior:

1. The execution of a behavior lasts more than 50% longer than during the training. To determine this fact, the wheelchair measures the duration of behaviors. If such an overflow has been detected, it is assumed that there was an error in the reproduction of the learned route.
2. The wheelchair finds different routemarks of the same type and switches to the next behavior. In this case, the erroneous execution is not de-

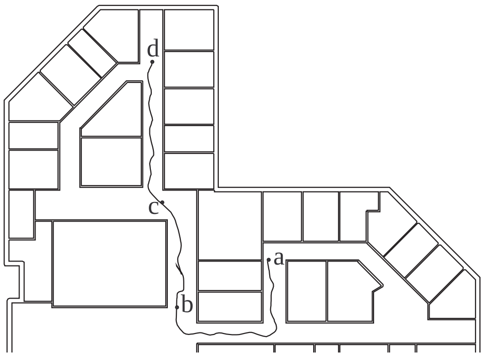


Figure 5 *An autonomous reproduction of a learned trajectory generated by the combination of four basic behaviors. a) Follow right wall. b) Follow left wall. c) Follow right wall. d) Stop.*

tected immediately but it can be expected that one of the subsequent behaviors cannot be completed and therefore will fail.

So, an error can only be determined if a behavior lasts too long, but the cause of this error can also be a defective execution of a previous behavior. Thus, a strategy for compensating errors must be able to correct errors in previous behaviors. If the wheelchair has missed some routemarks, it can track back the route segment and search again. If it has made an error in carrying out a behavior, it has no other possibility than to drive back to a position before the error and to try again. As it does not know where the error occurred, it drives back the last route segment and searches for the missing routemarks; then it repeats this segment. If this again results in an error, it drives back the last two segments and repeats them etc. If it has repeated the complete previous route without being successful, the execution of the route fails. Such failures can only be recovered from on the level of survey knowledge, e.g. by also back-tracking the previous route or by using a different one.

6 Results

Route Navigation. Although the wheelchair is 72 cm wide and 134 cm long, the basic behaviors have enabled it to drive through 94 cm wide doorframes and to turn into doors in a 176 cm wide corridor (Röfer, 1997b). It has been able to learn and to repeat routes consisting of several basic behaviors. For example, figure 5 shows a 60 m long trajectory that has been generated by concatenating four behaviors. The trajectory has been recorded by the wheelchair's onboard odometry on the second floor of our

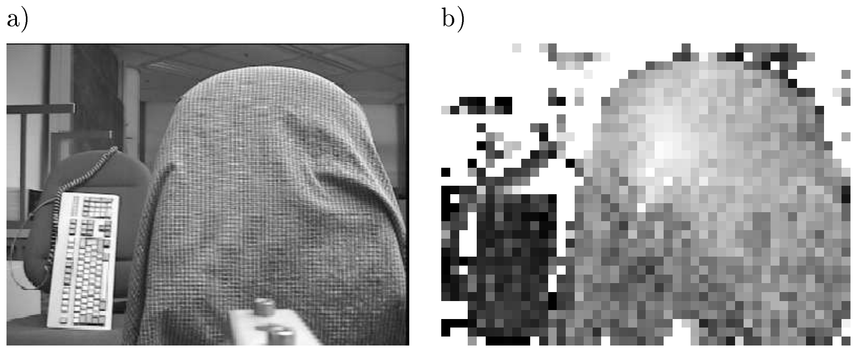


Figure 6 *Estimated depth in a real-world scene. a) The scene. b) The estimated depth. The darker the pixels, the farther away the objects. White pixels indicate impossible distance estimation.*

department's building. During the experiment, there were several obstacles on the floor that are not shown in the plan, e.g. tables, cupboards, and open doors, that the wheelchair bypassed. The mobile system has been able to recover from both types of possible errors, i.e. from missing routemarks and from the erroneous performance of behaviors. Both errors have been forced by hiding routemarks and blocking passages. An important result for future work with natural 3-D routemarks is that it is necessary to always have a wide selection of routemarks because the worst thing that can happen is that the behavior should be changed and no appropriate routemark to trigger this change is available.

Early Results in 3-D Mark Recognition. Currently, simulations have been conducted to judge the algorithm's performance for depth estimation. In these simulations, the camera approached a single wall perpendicularly. It turned out that the method is capable of estimating depth robustly in real time, but the depth values were quite noisy. Hence, further processing stages must be able to cope with noisy input. In figure 6, a real-world experiment is shown. The camera approached two objects—a shirt hanging over a chair-back and a keyboard on another chair (Figure 6a). Figure 6b shows the result of the depth estimation. As can easily be seen, the shirt is closer to the camera than the keyboard.

7 Conclusion and Future Work

This paper has presented a psychologically inspired navigation approach. A robust implementation of some basic behaviours and the recognition of routemarks enable a wheelchair to autonomously follow trained routes.

In the future, natural 3-D marks will replace the artificial routemarks. To achieve this, the distance images will be segmented into areas of equal relative motion. In each such area, discontinuities and extrema of depth and depth derivatives should be recognized, automatically selected, and utilized as 3-D marks. Early results on this field indicate that the presented algorithm is capable of estimating depth in real time, with high spatial resolution and robustly with respect to illumination, orientation, and noise.

Currently, a second autonomous wheelchair is set-up. This will allow to analyze the performance of the navigation approach if multiple wheelchairs navigate in the same terrain. As the routemark detection uses a passive sensing technique, i.e. video, it can be assumed that it will still work in such a scenario. However, the basic behaviors are based on sonar sensor that can influence each other. As such cross-talks always generate shorter distances than the undisturbed measurements, it can be supposed that multiple wheelchairs will avoid each other. The only sensor system that might fail is the collision detection because it may stop the vehicle in front of phantom obstacles.

Acknowledgement

The authors are supported by the Deutsche Forschungsgemeinschaft through the priority program "Spatial Cognition".

8 References

J. K. Aggarwal & N. Nandhakumar (1988). On the computation of motion from sequences of images – a review. In: *Proc. of the IEEE* **76**. 917–935.

U. R. Dhond & J. K. Aggarwal (1989). Structure from Stereo – A Review. In: *IEEE Transactions on Systems, Man, and Cybernetics* **19** (6). 1489–1510.

Ch. Herwig (1996). Visual Motion Processing for Active Observers. Ph. D. Thesis. In: B. Krieg-Brückner, G. Roth & H. Schwegler (Eds.): *ZKW-Bericht* (1/96). Zentrum für Kognitionswissenschaften. Universität Bremen.

B. Krieg-Brückner, Th. Röfer, H.-O. Carmesin, & R. Müller (1998). A Taxonomy of Spatial Knowledge and its Application to the Bremen Autonomous Wheelchair. In: Ch. Freksa, Ch. Habel, & K. F. Wender (Eds.): *Spatial Cognition*. Lecture Notes in Artificial Intelligence. Springer (*to appear*).

Th. Röfer (1997b). Routemark-Based Navigation of a Wheelchair. In: *Proc. Third ECPD International Conference on Advanced Robotics, Intelligent Automation and Active Systems*. Bremen. 333–338.