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Route-Based Robot Navigation

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The ability to navigate in known and unknown environments belongs to the key skills of today's mobile robots. Especially in structured environments, characteristics of the robot's surroundings can be used to simplify the task. In many everyday scenarios, *routes* constitute a good representative of the structural nature of the robot's world. In addition, a route description is an adequate means to specify the robot's locomotion. This article recapitulates the experiences and findings with respect to the route-based navigation of mobile robots resulting from the work of the Bremen project "Robot Navigation" within the framework of the priority program "Spatial Cognition" funded by the Deutsche Forschungsgemeinschaft (DFG).

1 Introduction

Within the framework of the priority program "Spatial Cognition" [4][3] the Bremen project "Robot Navigation" [1] develops a suite of basic behaviors [13] and navigation techniques. Experiments are carried out with the Bremen Autonomous Wheelchair "Rolland" (see Fig. 1 left) that serves as research platform on the one hand, and as a prototypical rehabilitation robot on the other hand [9].

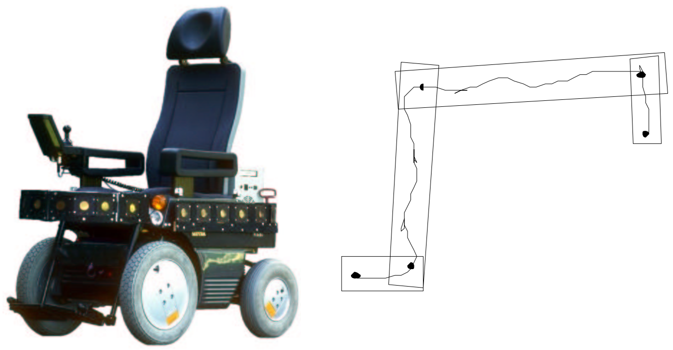

Figure 1. Rolland, the Bremen Autonomous Wheelchair, and the generalization of a motion track

This article recapitulates the relevant experiences and findings during the past six years: the underlying algorithm for the incremental generalization of traveled routes to a compact representation [11] is summarized. We show how these route descriptions have been used for route learning, "one-dimensional" localization, and navigating a robot by route instructions [10]. Current work deals with self-localization in large-scale environments [8]. We use a real-time capable probabilistic approach to absolutely localize the robot in a given representation of the world, a network of routes (the so-called route graph, cf. [15]).

2 Routes

The concept of a *route* is fundamental to our navigation approach. Definitions in the literature (cf., e.g., [5][6][15]) differ only slightly in details such as terminology and notation, but usually agree on the basic assumption that a route is a sequence of decision points that are connected by segments. Depending on the problem domain, this general definition can be instantiated for different real world scenarios, such as railroad connections between large cities, paths in a park, or corridors in a tax office building.

2.1 Representation

For the application scenario we pursue (see section 1), a more specific definition of a route is used. Accordingly, a *route* is a sequence of straight segments that intersect under certain angles. Since almost no robot is able to travel along a straight path (especially in dynamically changing environments), such a route represents an abstraction of a real movement of the robot:

$$R = \langle C_i \rangle, \text{ where } C_i = (\alpha_i, l_i),\ i \in \{1 \dots n\} \tag{1}$$

The route R is a finite sequence of so-called *corners* C_i, each of which is a pair of the angle α_i between the incoming and the outgoing straight segment of this corner, and the length l_i of the outgoing segment. As an example, consider a route specified as "(0°, 800 cm), (89°, 345 cm), (-83°, 566 cm)".

The acquisition of such a route description is accomplished by the incremental generalization of traveled tracks introduced by Röfer [11]. The idea is to generalize the locomotion of the traveling robot during runtime to an abstract route description. On the right, Fig. 1 shows the locomotion of the robot as recorded by its odometry system as a solid curved line. The corners recognized by the generalization algorithm are depicted as circles. The rectangular boxes represent the so-called acceptance areas: As long as the robot remains within such a region, it is assumed that the robot is still located in the same corridor. The width of the rectangular boxes is determined with the help of a histogram-based approach from the measurements of two sonar sensors mounted on the wheelchair's left- and right-hand side chassis. The generalization of the traveled track is carried out incrementally, i.e. while the robot moves.

2.2 Self-Localization in Routes

In [11], it is shown how two such route descriptions are matched to perform a "one-dimensional" self-localization along the route that is followed by the robot: In a teaching phase, the wheelchair is controlled along a route, e.g. by manually steering it with the joystick. The system records its dead reckoning positions. As the odometry data can consist of many measurements, it is *generalized* to generate a compact representation of the route, as presented in the previous section. This information is stored, and it is used as reference for future (autonomous) runs along this route.

In such a future run, the dead reckoning data is recorded, too. It is generalized the same way as during the teaching phase. The description stored always represents the complete route whereas the current track only stands for the part of the route traveled so far. Therefore, the current description can only be matched with the beginning of the stored one. The segment in the stored representation that is matched with the last segment of the current track is called the current segment. Together with the length of the last segment in the current track, i.e. the distance to the last corner, this defines the wheelchair's current position with respect to the route representation stored.

2.3 Basic Behaviors

Basic behaviors such as *wall-following* or *turning-on-the-spot* can be used to provide the robot with a high degree of robustness [7]. Since a basic behavior is a rather abstract description of the robot's locomotion, the navigation success is comparatively independent of the exact structure of the environment. Therefore, minor changes such as moved furniture or dynamic "obstacles" such as people walking by do not cause any problem.

2.4 Navigation along Routes

The integration of the route generalization method and the basic behaviors results in the route navigation approach presented in [11]. It works as follows: when the wheelchair travels using basic behaviors such as wall-following, its movements reflect the structure of the environment. The dead reckoning system of the wheelchair can record these movements. The resulting motion tracks can be employed to generate representations of the routes the system has followed. Positions along the route where the wheelchair switched the current basic behavior, e.g. from corridor-following to door-passage, are stored with the route. If the system drives along a route a second time, its dead reckoning system will produce a very similar track. Now, the wheelchair can choose the behavior stored for the current location and autonomously follow the route.

Another route-based navigation approach is presented in [10]. A mobile robot is provided with a route description in a formal language. The instruction makes use of coarse and qualitative expressions such as "left" or "far". In addition, it contains behavior- and environment-related information. While traveling, the wheelchair perceives its surroundings by sonar sensors and extracts information about special landmarks, the controlmarks and the routers. This is done by an algorithm based on line detection which is borrowed from the field of image processing. Depending on the current situation, the robot chooses one of the available basic behaviors, e.g. *corridor-following*, to follow the route in accordance with the previously given instructions.

3 From Routes to Route Graphs

As summarized so far, the developed techniques enable a robust navigation of a mobile robot along routes that consist of straight segments which meet under certain angles. Self-localization is done by matching a previously learned route description with the incrementally generalized one. Adequate navigation skills are provided by switching between basic behaviors while traveling on a route. Even the detection of navigation errors is possible if the target route and the actual route diverge.

Nevertheless, the route concept is a "one-dimensional" one. As is, it is not general enough for the complex large-scale navigation tasks we intend to solve. Therefore, we extend the single route navigation to the navigation in networks of routes, the so-called route graphs [15].

3.1 Representation

As a model of the environment, we use such a route-graph. It is a hybrid topological-metric map. The nodes of a route graph (see Fig. 2) correspond to decision points in the real world: hallway corners, junctions or crossings. The edges of the graph represent straight corridors that connect the decision points. In addition to the topological information, the route graph contains (geo-)metric data about the length of the corridors as well as about the included angles.

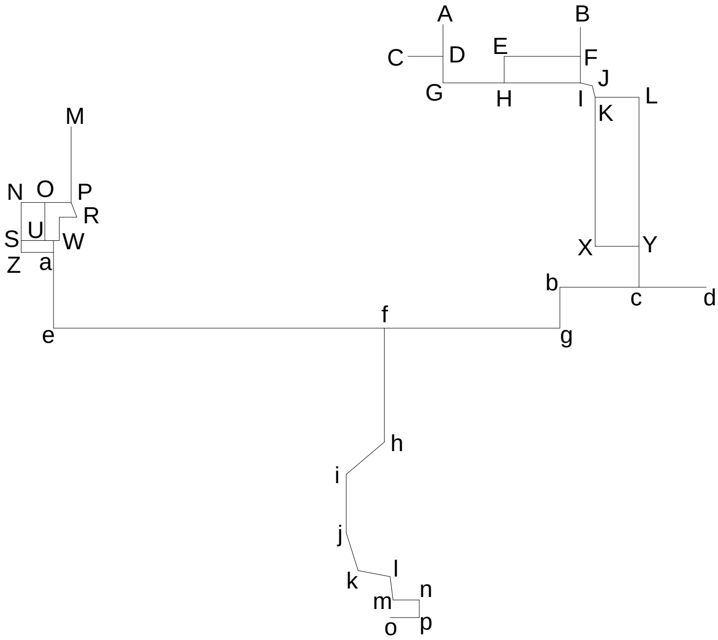

Figure 2. A Route Graph. The depicted route graph represents a part of the campus of the Universität Bremen. It consists of 42 graph nodes and 128 junctions. The represented corridors range in length from 4.3m to 179m.

In contrast to common grid-based representations [2][14], such a data structure is much easier to handle with respect to the required amount of computing time and memory. For example, the campus environment depicted in Fig. 3 *left* is represented as a list of only 128 so-called junctions (see Fig. 2). A junction J is defined by its incoming corridor IJ, the outgoing corridor JK, the angle γ enclosed by both corridors, and the length d of the outgoing corridor. Then, the set of all junctions is the route graph G:

$$G = \{J_i \mid J_i = (I_i, K_i, \gamma_i, d_i),\ i \in \{1 \ldots m\}\} \quad (2)$$

3.2 Self-Localization in Route Graphs

We use a probabilistic approach (for an overview on probabilistic algorithms in robotics, see [14]) to ongoingly determine the hallway H (represented by an edge in the route graph), in which the robot is most likely located at a certain moment in time [8]. Since the distance already traveled in H is also known, an additional offset can be derived. As a result, the position of the robot within the hallway can be determined precise enough for most global navigation tasks. The precision is limited by about half of the width of the corridor the robot is located in. Due to the modeling of the environment and the robot's locomotion, our algorithm turns out to be rather insensitive to odometry errors (see Fig. 3 right: the odometry error accumulates to 290m after 2.2km travel distance), because the offsets normally represent only short distances that result from accumulating straight movements, and almost no rotational motion which often causes dead reckoning errors.

The algorithm continuously matches the current route generalization with the route graph and is thus able to pose a hypothesis about the wheelchair's position. The sensor requirements are very low (odometry, two sonar sensors). Furthermore, the approach is open for extensions, e.g. adding information to the route graph that helps to disambiguate situations of perceptual aliasing.

In spite of the poor odometry data, experiments on the campus of the Universität Bremen show that the wheelchair is able to robustly self-localize on a 2.2 km long route through seven buildings, along several large outdoor “corridors”, and over open places (see Fig. 3 left).

4 Conclusion

The results of the Bremen project “Robot Navigation” within the framework of the DFG priority program “Spatial Cognition” show that routes constitute an adequate basic data structure for mobile robot navigation in structured environments. On the one hand, they are suitable as descriptions of the environment in form of route graphs. On the other hand, they provide a good characterization of a robot’s locomotion in form of generalized descriptions of the motion track. Matching both models in a probabilistic approach is a robust self-localization method for mobile robots in “corridor-rich” scenarios.

5 References

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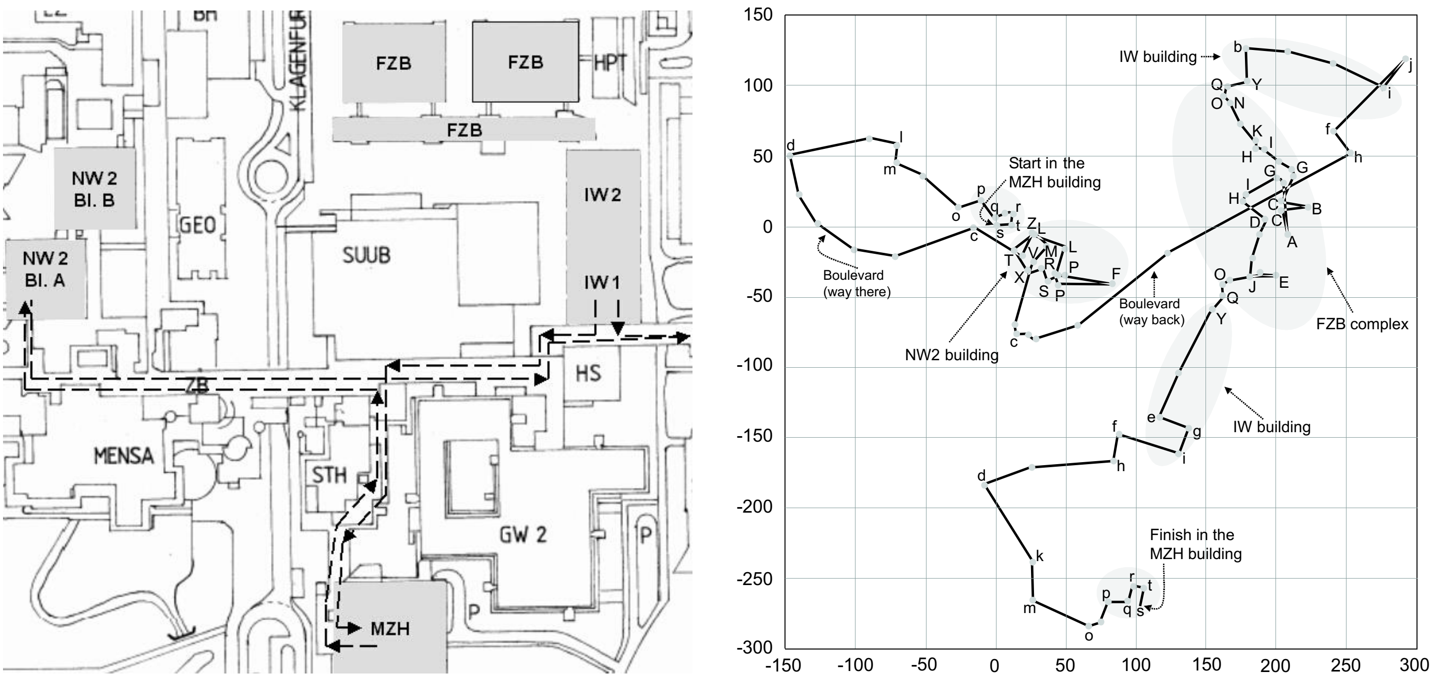

Figure 3. Route across the campus and the generalization of the odometry scan