Autonomous Navigation of RFID-Sensing Robots

--- Information Ensuring for the Visually Impaired (2) ---

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Abstract - *The construction of information ensured environment for the visually impaired (say, in the college life) combining data carrier and network technologies includes the problem of obtaining and conveying environmental information. As the visually impaired have keen difficulties in sensing changes of surroundings, in order to assist them we usually need an interface (say, a guide dog) between people and the environment. We put RFID tags on surrounding objects so that we can treat them as landmarks of the environment. Then we can design autonomous robots to sense the changes of locations of objects and situations. In this paper we describe a general navigation algorithm of such robots based on distance information obtained, say, by super sonic sensors which are equipped on the robot. Our algorithm is designed on the so-called Distance Field Space Model (DFM), which can be considered as a natural description of objects and space on the basis of a fuzzy set theory. Though major part of this paper is devoted to the development of the navigation principle based on DFM, our RFID-sensing robots are not equipped with this algorithm yet.*

Keywords: Distance field space model, robot, RFID, passage route finding, visually impaired.

1 Introduction

The Distance Field Space Model (abbr. DFM) was presented by the authors as a space description model for recognition, understanding and control of spatial environment [1],[2]. DFM is able to treat both the spatial objects and their surrounding space concurrently and consistently, by introducing hypothetical "distance field" attributed to the embedded real objects.

As a typical problem involved in spatial environment, we know the passage navigation of a robot. In this problem, the navigation first requires designing optimal passage routes for a robot to move around the work space efficiently, while avoiding the obstacles. There are two cases: the passage domain is either known or unknown to the robots. This means that the knowledge of the passage environment including obstacles and passage area is given beforehand or not. We say the former "known environment" and the latter "unknown environment" [3]. Several papers on search algorithms of optimal routes under unknown environment have been presented, where they use conventional geometric models as the world (space) model and search the routes by iteratively calculating the distance between robots and obstacles [4]-[6]. However, these seem to be restricted to the limited application and confined to the 2-dimensional space with simple shaped obstacles and of simple allocation. This result is due to the fact that capability of the conventional models is limited with respect to recognition and understanding of the spatial environment.

In this paper we present a description of the navigation of autonomous robots based on DFM mentioned previously as the space model. As we will see, DFM gives a fuzzy set description of spacial objects (distance datum in DFM represents a concrete value of the membership function of a fuzzy set system). Though no our robot is equipped with our navigation algorithm yet, our computer simulation shows that our method is efficient, and so we hope it applicable to our RFID-sensing robots, described in [7]. The formulation we borrow largely from [3].

2 Distance Field Space Model (DFM)

The notion of DFM is based on an observation that the skill of computer's eyesight is limited to sense only positional relations to targeted objects at a reference spatial point. Positional relations between the targeted objects and a reference point we represent by the so-called "distance field vector" described below. So in this model you are given a set of distance field vectors at any reference point in the space. The computer is further assumed that it grasps the objects by gathering, assembling and analyzing local information represented in DFM. Thus, the distance field represented by the distance field vector is the key concept of DFM.

Given an object G and a reference point P in a space, the "distance field" of the object G with respect to the point P is represented in DFM by a "distance field vector" (DF-vector) [1],[2] (4-tuple) as follows (See Fig. 1).

(IO, d, Q, KIND) (1)

Where,

IO (IN/OUT datum) :
"IN" if the point P belongs to the object G, "OUT" otherwise.

d (distance datum) :
the distance or its lower approximate between the point P and the boundary of the object G.

Q (nearest-point datum) :
one of the nearest points to the boundary, which takes the value d, or "NIL" if the point Q can not be found.

KIND (category datum) :
"1" if both the distance d and the nearest point Q are set correctly, or "2" otherwise.

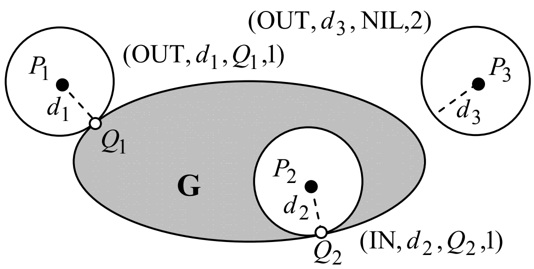

Figure 1. Distance field

DF-vector is a basic data structure in DFM. By DF-vectors an object and the space in which it is embedded are represented in an integrated way. This representation is simple, robust and of a better performance both in geometric modeling and space reasoning [8].

A fuzzy interpretation of DFM

We briefly review that DFM allows a fuzzy set interpretation of objects in a most natural way [8].

Let G be a (crisp) set in Euclidean metric space E^n. For simplicity assume that E^n is divided into interior (G^i), exterior (G^e) and boundary ($\dot{G}$) with respect to G. Define a fuzzy set $[G]$ on G if there exist a membership function $\mu_{[G]} : E^n \to \boldsymbol{R}$ satisfying the following relation for each $x \in E^n$: Put $d = \mu_{[G]}(x)$. Then

$$\begin{cases} d > 0 \text{ and } B(x,\, d) \subset G^i & \mathit{if}\ x \in G^i, \\ d < 0 \text{ and } B(x, -d) \subset G^e & \mathit{if}\ x \in G^e, \\ \qquad d = 0 & \mathit{if}\ x \in \dot{G}, \end{cases} \tag{2}$$

where $B(x,\, d)$ denotes d-neighborhood of x, i.e., $B(x,\, d) = \{P : \overline{xP} < d\}$. We show that DF-vector gives a fuzzy membership function on G.

[Assertion] The distant datum d of G with respect to x gives a fuzziness of x for G.

Indeed, it is easy to check that the following function f is a fuzzy membership function on G:

$$f(x) = \begin{cases} d & \mathit{if}\ x \in G, \\ -d & \mathit{if}\ x \in G^c, \quad \mathit{where}\ G^c = E^n - G. \end{cases} \tag{3}$$

By this correspondence, fuzzy set operations $\cup$ (union), $\cap$ (intersection), ^{c} (complement) in the usual sense can be done freely in DFM.

In this paper we adopt DFM as the world model. So we assume that at any reference point a set of DF-vectors is given (though in the reality, distance together with nearest-point data are sometimes hard to obtain).

3 Optimal passage route search under known environment

As the working space domain is known to the robot beforehand, it is basically possible for the robot to trace the feasible work region, which corresponds to the compliment space of obstacles.

Given two points in it, the problem is to find an optimal passage route from one point to the other point. An optimal route is a feasible route that minimizes the penalty cost which is defined by the sum of the total length of the route and the distances between the robot and obstacles. As a fundamental algorithm, we take the A* algorithm and reformulate it in DFM (the modified one we call the Distance Field A* algorithm, or in short DF-A* algorithm). A candidate path consists of a set of linear segments between the two fixed points, generated iteratively in the course of DF-A* algorithm. Thus, the whole set of candidate paths is limited to a subset of the all feasible segmented paths and is not the whole set of the feasible paths. So the term "optimal" in this paper is confined locally to DF-A* algorithm.

3.1 Building a model for passage route search problem

Let $(P_0, P_1, P_2, \cdots, P_n)$ be a series of points in the compliment space O^c of the obstacle O, where P_0 and P_n are fixed as the start point P_S and the goal point P_G, respectively. A path L is defined as a series of linear segments $L_{i,i+1}$ connecting adjacent points (P_i, P_{i+1}) ($i = 0, \cdots, n-1$) (See Fig. 2).

First of all, the segment cost $w_{i,i+1}$ is attached to each element $L_{i,i+1}$ of a path as follows :

$$w_{i,i+1} = \begin{cases} 1/d_{i,i+1}^2 & \cdots \quad R_{\min} > d_{i,i+1} \\ d_{i,i+1}/R_{\min}^3 & \cdots \quad R_{\min} \le d_{i,i+1} \end{cases} \tag{4}$$

where $d_{i,i+1}$ is the length (distance) of the segment $L_{i,i+1}$ and $R_{\min}$ is the lower limit of the effective motion radius of the robot (roughly its size). Then, the total cost of the path L is defined as a simple sum of the segment costs :

$$\tilde{g}(L) = \sum_{i=0}^{n-1} w_{i,i+1} \tag{5}$$

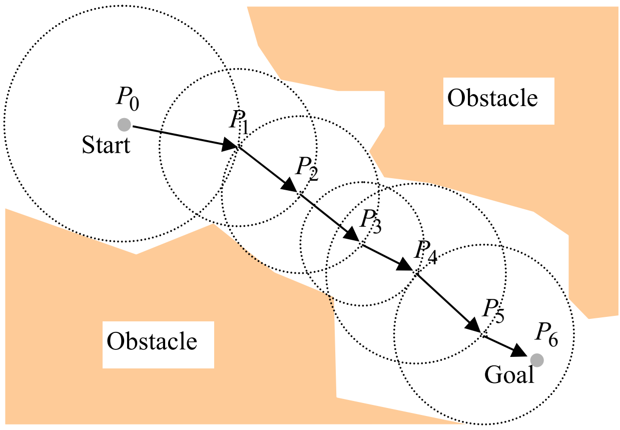

Figure 2. Passage route

Finally, the passage route search problem between P_S and P_G is defined as a problem to find a path L that minimizes the cost $\tilde{g}(L)$.

3.2 DF-A* algorithm

In order to exploit the A* algorithm, it is necessary to adopt a method to improve a solution, while generating feasible partial-paths iteratively. Here it is formulated as DF-A* algorithm.

First of all, its iteratively updated network is formulated by a 4-tuple as follows:

$$N = (V, E, g, f) \tag{6}$$

where, V : the node set, E : the edge set. g , f are mappings: $V \to \mathbf{R}$ from $\mathbf{V}$ to the real number field $\mathbf{R}$. $g(i)$ is the cost of an optimal route from P_S to P_i . $f(i)$ is a estimated cost from P_S to P_G via P_i and of a form $f(i) = g(i) + h(i)$, where $h(i)$ is a function evaluating the cost of the route from P_i to P_G heuristically by using the distance $dis(i,G)$ between P_i and P_G :

$$h(i) = dis(i,G)/R_{\min}^3 \tag{7}$$

Now, DF-A* algorithm is formulated by the following two phases.

(1) Search phase

[Step 1] Initialize the network N by

$V \leftarrow \{P_S\}$, $E \leftarrow \phi$, $g(S) \leftarrow 0$, $f(S) \leftarrow h(S)$.

[Step 2] Choose a node i of the network N such that the node i takes the minimum $f()$ value among yet undeveloped nodes. Compute d_i of the distance field at the node i and the distance $dis(i,G)$.

[Step 3] If $d_i \geq dis(i,G)$, then there exists a line segment between P_i and P_G which is free from the obstacles. Update the network N so that

$V \leftarrow V \cup \{P_G\}$, $E \leftarrow E \cup \{(i,G)\}$, $g(G) \leftarrow g(i) + h(i)$,

$f(G) \leftarrow g(G)$.

Then go to Step 5.

[Step 4] If the node i has the parent node, let it be k or ϕ (null) otherwise. Draw a circle with the radius d_i and with the center i , and place a given number ($= N_{ang}$) of points on the circle, distributing equi-angularly. Update the network N for each such point j that the inner product of the vectors (i,j) and (k,i) is non-negative. Incidentally, if $k = \phi$, then apply it for all the points j (See Fig. 3):

$V \leftarrow V \cup \{P_j\}$, $E \leftarrow E \cup \{(i,j)\}$, $g(j) \leftarrow g(i) + w_{i,j}$,

$f(j) \leftarrow g(j) + h(j)$.

Then go to Step 2.

[Step 5] In the network N , find the route back to the start node P_S from the goal node P_G , the reverse of which is our solution. Stop.

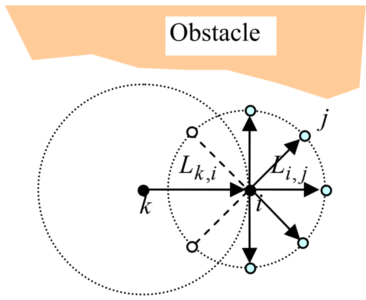

Figure 3. Create child nodes j from node i

(2) Smoothing phase

We replace any two consecutive segments $L_{k,i}$ and $L_{i,j}$ of the solution of the search phase by the segment $L_{k,j}$ concatenated by $L_{k,i}$ and $L_{i,j}$, if $L_{k,j}$ does not collide with the obstacles; that is, if the segment $L_{k,j}$ is included in the union of the two disks centered at k and i .

4 Navigation and sensing model

Basically we follow the approach in [3]. However, our method is to be considered in computer simulation and will be realized by real motion of the test robots called ER-1 produced by Evolution Robotics Inc. [9].

4.1 Navigation model

As shown in Fig. 4, the navigation model under unknown environment is composed of two phases: "building environment" based on sensing for inference of the environment and "robot navigation", where passage route planning and robot motion are conducted according to the updated environment.

(1) Sensing (Simulation and real sensors)

Super sonic sensors infer the distance between the robot and the surrounding obstacles according to the sensing model of range measurement to be described in the section 4.2. In the case of unknown environment, the estimate by inference is taken into consideration.

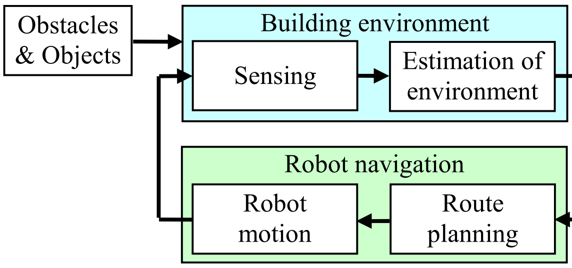

Figure 4. Navigation model

(2) Estimation of environment

According to the sensed data, new "feasible region of motion" and "infeasible region of motion" are constructed. This is to be detailed in the next section 4.2.

(3) Route planning

This planning determines an estimated optimal route from the present robot position to the goal, using inferred spatial information, especially on the infeasible motion area. In this planning, the inferred infeasible motion area is taken as the present known environment and DF-A* algorithm is applied for searching the route. When no route is found here, the navigation stops as infeasible.

(4) Robot motion

First, the robot moves toward the end of the first segment along the segment as far as the end is not reached. In the meantime, if the robot collides with an obstacle, then the point is taken as next sensing point, or else if the end point is the goal, then the robot stops there and the passage completes successfully, or else check whether the point is inside the feasible motion area or not. If the end is outside, then the point is taken as next sensing point, or else do the same operation for next segment.

Finally, while continuing robot motion, it reaches the goal and completes the simulation, or stops temporarily at the next sensing point. In the latter case, the simulation goes back to the building environment phase and continues.

4.2 Sensing model

Assuming that supersonic sensors are allocated in the equal angular intervals along the cylindrical boundary of the robot, we describe a range sensing model of the sensor system. First we review shortly the model in [3]. Then we introduce our model based on DFM.

In the model in [3], the credibility of the estimated range for some obstacle is considered as follows, according to the physical characteristic of supersonic sensors.

(1) The existence is confined to the angular width ($\pm\Delta\theta$) with respect to the emitted beam axis.

(2) Even if the range signal r is given, the existence is taken as ambiguous in the depth ($\pm\Delta r$) with the center r.

(3) No reflected beam is available for the obstacles apart more than the distance ρ_v from the sensor.

They introduced two fuzzy sets: "Occupied" (the point inside obstacles) and "Empty" (the point outside the obstacles) by defining respective membership functions in a cylindrical coordinate.

Interpreting DFM as the fuzzy space model, a concept similar to the sensing model in [3] can be implemented naturally by using primitive objects of DFM. We introduce two kinds of sensing models, an "optimistic model" which stands optimistically for the robot, and a "pessimistic model" on the other hand. Note that in either case, no primitives are generated for a sensor ranging $r > \rho_v$.

(1) Optimistic model

As primitive objects representing the optimistic fuzzy sets, the "optimistically occupied" ΔO and "optimistically empty" ΔE as shown in Fig. 5, are taken respectively. This interpretation is valid because the distance measure (the distance datum of a DF-vector) can be treated as a fuzzy membership function [8]. Incidentally, the term "optimistic" is applied to the treatment that the obstacles possibly exists only in the area $\rho > r$ where r is the sensed range, and its inside ($\rho < r$) is treated as an empty region.

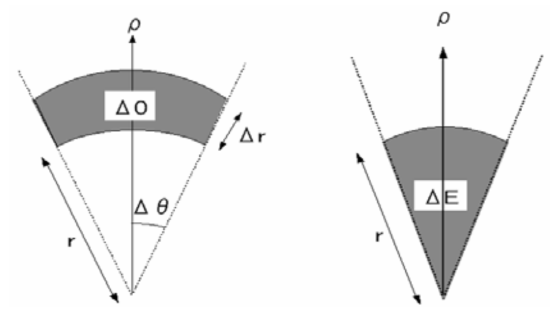

Figure 5. Optimistic model

(2) Pessimistic model

As primitive objects representing the pessimistic fuzzy sets, the "pessimistically occupied" δO and "pessimistically empty" δE as shown in Fig. 6, are taken respectively. In this case, the occupied region is taken excessively large as δO and on the contrary, the empty region is excessively small as δE, which means pessimistic for the robot.

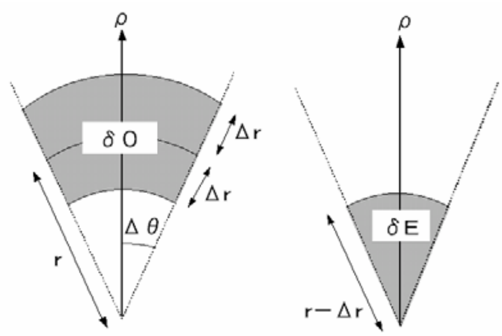

Figure 6. Pessimistic model

5 Estimation of the environment and robot navigation

By inference of environment based on the sensing models, the passage environment is estimated. In this section, the inference algorithm for the infeasible region of motion O_k and feasible region of motion E_k, and the robot navigation using the estimated environment are discussed.

5.1 Estimation algorithm

First of all, at the present position of robot, all the sensed data $(\Delta O, \Delta E)$ and $(\delta O, \delta E)$ are stored in time series. Moreover, at any sensing point k, sensors more than one are assumed to be participating in sensing. That is, from the start to the point k, let n-sets of data $(\Delta O_i, \Delta E_i)$, $(\delta O_i, \delta E_i)$, $i = 1, \cdots, n$ be stored in the sensing database. Then, at the point k, the infeasible region of motion O_k and feasible region of motion E_k are estimated as follows.

$$O_k \leftarrow \phi, \; E_k \leftarrow \phi; \tag{8}$$

$$O_k \leftarrow \Delta O_i \cup (O_k \cap \Delta^c E_i), \quad \text{for } i = 1, \cdots, n; \tag{9}$$

$$E_k \leftarrow \delta E_i \cup (E_k \cap \delta^c O_i), \quad \text{for } i = 1, \cdots, n. \tag{10}$$

Thus, the region O_k is estimated optimistically for the robot. On the contrary, the region E_k is estimated pessimistically for the robot.

5.2 Navigation algorithm

The outline of the algorithm is already described in the section 4.1. The navigation phase is composed of the passage route planning and the motion simulation of the robot based on the planning. In the route planning, under the given region O_k, an optimal route from the point k to the goal is searched by the route search algorithm under known environment. Since this route is an estimate of feasible optimal route, for the infeasible region O_k, its complement O_k^c of feasible region is taken optimistically. Then, according to the path obtained in the planning, the robot is move by 1 segment at most on the path, while the robot is confined in the region E_k. Thus, the region E_k is estimated so narrowly as re-tries due to collision with obstacles do not often occur.

5.3 Numerical simulation

The scene shown in Fig. 7 is a path search problem taken for numerical experiments (where the motion space is assumed the region of a square of size 30 in edge, $N_{ang} = 8$, and $R_{\min} = 1$).

In Fig. 8-(1), $\cdots$,(6) we show the process of the passage route planning and the robot navigation according to the sensing model and to the navigation algorithm. You may read Fig. 8-(k) ($k = 1, \cdots, 6$) as follows.

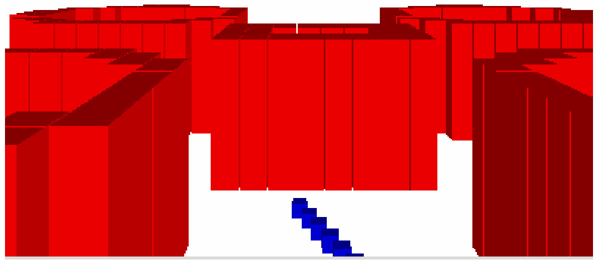

Figure 7. A simulation scene

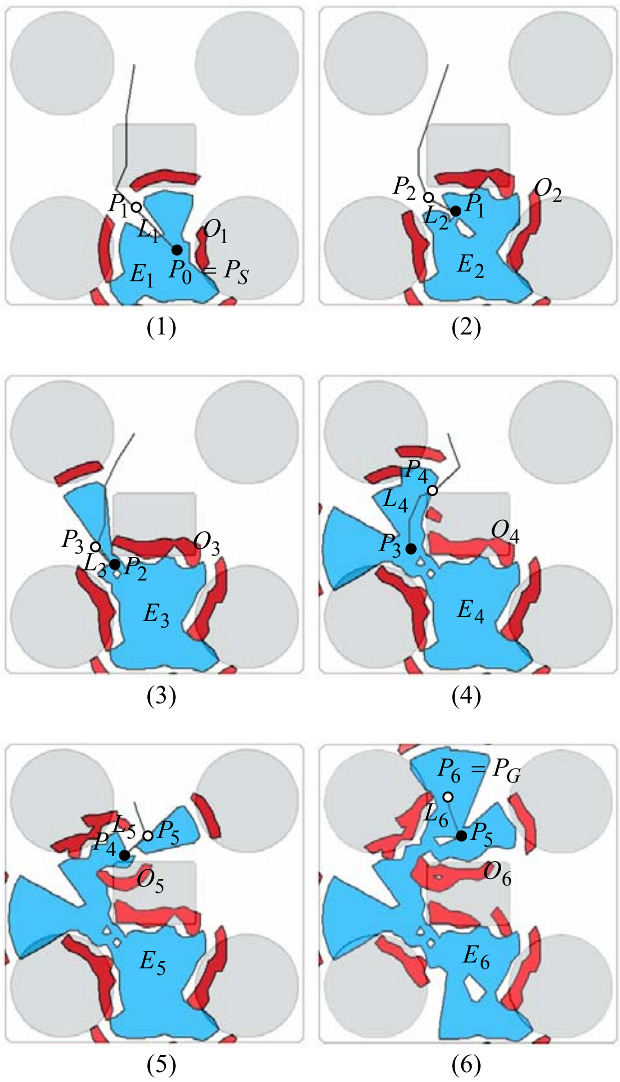

Figure 8. Navigation process

Each figure shows the resulted path L_k of the route search from P_{k-1} ($P_0 = P_S$) to the goal $P_G = P_6$ assuming the estimate of infeasible region O_k (red region) as the known environment. Incidentally, O_k is estimated by updating O_{k-1} using the sensed data at the point P_{k-1} by eq. (9). The passage route on the path L_k is solved according to the navigation algorithm based on the region E_k (blue region). Similar to updating O_k, the region E_k is estimated by updating the E_{k-1} using the sensed data at the point P_{k-1} by eq. (10).

Our method easily realizes an algorithmic variation considering the effect of lost data appeared in [3]. This is the case when old sensed data are left behind. Instead of using all the sensed data: $(\Delta O_i, \Delta E_i)$, $(\delta O_i, \delta E_i)$, $i = 1, \cdots, n$ in the estimation of O_k and E_k, we use only the newest m data (where $i = n - m + 1, \cdots, n$).

As seen from the simulation result, paths are well smoothed and have no unrealistic, unnatural parts. Though the performance is not especially analyzed, the response is immediate and the algorithm is thought to be well for real use. In the case of lost data, it is expected for a large memory saving and high performance.

6 Conclusions

On the basis that DFM can be interpreted as a fuzzy space model under known environment and the fact that the passage route problem can be solved by the DF-A* algorithm, we have developed both a search algorithm of the passage route and a robot navigation algorithm under unknown environment. Our method, as it is based on DFM, seems to be simpler and more flexible than one stated in [3]. These features are derived from the fact that DFM can be interpreted as a fuzzy space model.

We have implemented a naive navigation algorithm in our prototype system where several robots move around to get environmental information for the visually impaired by sensing RFID tags (i.e., sensing locations of objects which are subject to occasional changes). The implementation and the experiment of the algorithm presented here on the RFID sensing robot are not yet completed (Fig. 9 shows an experiment using our RFID-sensing robots) [7]. In Fig. 10 we show two landmark scenes taken from our robot ER-1 (actually it can register any scene as a landmark). A predefined landmark serves to calibrate current position of the robot which is usually supplied by odometer data (with cumulating errors). For an efficient navigation we may need to incorporate other data than distance as well.

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Figure 9. An experiment using RFID-sensing robots

Figure 10. Two landmark scenes

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