Mobile Robot Navigation in Enclosed Large-Scale Space*

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Abstract – **In a large-scale space, navigation may occur among very dispersed landmarks, further apart than the range of sensing of an autonomous vehicle. In this work we investigate the feasibility of construction of a landmark-based cognitive map, whose elements are the obstacles perceived by a robotic vehicle during exploration of an unknown, large-scale environment. This cognitive map can then be used as an aid for goal-oriented navigation in such a challenging environment. A map construction algorithm is described suitable for a mobile robot with the ability of temporarily marking a single location in an enclosed environment containing polygonal objects. The algorithm is being verified with a LEGO-Technic –based autonomous vehicle, equipped with a 2 d.o.f. arm and relying on inaccurate odometric and short-range proximity sensing. In spite of its limited and inaccurate internal and external sensing abilities, basic skills experimentally demostrated by the robot include pick-and-place of a portable marker, obstacle detection, as well as characterization and recognition of polygonal objects. These skills, in conjunction with the approximate odometric measurements collected by the vehicle, also represent the repertoire of behaviors exploited in map-assisted navigation.**

Introduction

In a large-scale space, structure is at a significantly larger scale than the observations available at an instant [12]. An extreme large-scale space condition occurs in navigation among very sparse landmarks, further apart than the range of sensing of an autonomous vehicle. Human examples of these situations could be the naive's view of the desert, driving in the fog, walking in an unknown urban setting. The invariant concept conveyed by these examples is the total lack of distinctive reference elements for a large fraction of navigation time.

While navigation in large-scale space has been addressed at varying extent by a number of researchers (e.g., [8, 11, 12, 14]), this emphasis on the lack of continuity in the flow of exteroceptive perceptual data available to the robot is peculiar to our research. Of course, this is a significantly aggravating condition and may prevent applicability of previously proposed methods and algorithms. In our minimalist approach we also rule out the use of a global, albeit proprioceptive, sensory device such as a compass. A compass is used instead in related works such as [12] and [14].

An obstacle-landmark, when found, could itself be at a larger scale than the robot's perception, so that a dedicated exploration subtask must be undertaken in order to locate the robot with respect to the landmark in a meaningful way. However, obstacle-landmark exploration is characterized by a local continuity in the flow of exteroceptive perceptual data, thus identifying a distinct phase of the overall navigation task. Hence, within this phase exploration can take advantage of techniques described in the literature for acquisition and integration of mapping data [8, 14].

Of course, a given environment appears to a lesser or greater extent as a large-scale space depending on the sensing capabilities of the robotic agent. Autonomous execution of complex tasks always involves exteroceptive sensing devices. While sensing is a mandatory component for (and largely contributes to) the degree of autonomy and efficiency of a robotic agent, more sensing does not always imply increased efficiency or reliability [10]. For witty, amusing perspectives on "sensor abuse" see [13, 15]. Humans do exhibit, at least to a certain degree, the ability to navigate among dispersed landmark even lacking a continuous exteroceptive information flow. What are the basic ingredients needed to achieve a similar capability in an autonomous vehicle?

In a large-scale scenario like the one depicted, goal-oriented navigation requires the availability of a *cognitive map* where the perceptual evidences, stemming from a preliminary exploration activity or collected during the navigation task, are integrated. The goal of our work is to explore the feasibility and effectiveness of landmark mapping and navigation at the lower end of the robot complexity spectrum, namely with a behavior-based mobile robot equipped with limited and local perceptual abilities. To carry out the navigation task the robot first develops an internal representation of the environment based on the directly perceived features of objects. This representation is then exploited as a resource in the actual course of navigation. While limitations in navigational performance are to be expected, the achievements of the robotic agent are to be contrasted against its very low cost and intrinsic "near-sightedness".

Literature Review

Our work bears obvious relationships with the large body of of behavior-based mobile robot research (e.g., [2, 3, 16]) inspired by the early work in [4]. In this section we briefly comment on those papers more directly related and influential to our research.

In [14] a convincing demonstration of behavior-based map construction and navigation is given. However, at least to our understanding, in Toto's operation as illustrated in the paper there is a constant flow of landmark-related percepts to be installed in the map, and it is not clear how the robot would behave if this condition were not satisfied by the environment. Furthermore, Toto also uses a 4 bit compass, thus has at least some approximate global information constantly available.

*Partial support for this research has been provided by C.N.R., Italy, under "Progetto Finalizzato Robotica", grant N. 92.01054.PF67, and under Special Program, grant N. 92.00026.CT12, by NASA Grant NGT-40015, and by the Dept. of EE, UF.

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Large-scale space navigation is also the subject of the work in [8, 9]. However, in those papers the authors take a different approach, and model the world as a graph whose nodes are the only meaningful locations in the environment and whose edges are the finite number of "moves" available at any location. A major emphasis of the papers is on the complexity issues of the mapping and navigation algorithms within this graph-theoretic setting. In spite of the hints given in the paper, there are only a few real-life situations that can be modeled in this way. The ones we could think of are a sewer and an underground, but in general both nature and humans tend to develop more varied environments, too rich to be usefully modeled as proposed in the paper. Furthermore, in graph-like worlds the continuity requirement is shifted from the sensors to the environment itself.

One of the results in [8] is that at least a marker is needed for self referencing in a graph-like world lacking any metric information. As pointed out in [9], fairy tales abund with examples of the use of markers of various sort for navigation purposes. We have capitalized upon this idea, in that a marker is exploited during exploration of an obstacle-landmark for self-referencing of the vehicle and to overcome its sensing deficiencies.

Finally, our work largely consonates with [1] and [11], especially in the exploitation of the cognitive map as a resource for navigation rather than for the generation of a rigid plan. This approach allows dynamic aspects such as world changes and navigation errors or other contingiencies to be dealt with at execution time.

Landmark Navigation

The universe of a robot derives from what it can perceive with its internal (proprioceptive) and external (exteroceptive) sensing. We assume that the robot can only perceive a portion of its universe at any location and point-in-time and that its perception possesses limited range and precision. For navigation, the robot must move within its environment without becoming disabled and answer

1) Where am I?
2) Where do I go from here?
3) How can I get there from here?

Except for the case where the robot possesses an exact coordinate map and can perform exact measurements, all these questions imply object recognition capabilities. Object recognition, in turn, implies some form of internal representation of the entities in the environment (location, landmark, or feature), either in software or in hardware.

Our approach to mapping and navigation emphasizes finding and identifying obstacle-landmarks. All target locations must be a perceived feature of a known obstacle-landmark. This emphasis on landmarks as places contrasts sharply to the use of landmarks in [5] as place resolution or position correction data.

The robot cannot locate an open area target using the landmark paradigm. The command "Go to a place in an empty region of the room" has no meaning to the robot because the empty region is not an obstacle-landmark. The landmark navigation approach possesses great robustness and simplicity. Further, autonomous construction of landmark maps appears to be much easier to develop and places less demands on the sensor suite of the robot.

In the following sections we take a robot designed for other purposes [6, 7] and demonstrate how it can be employed to construct a landmark map of its environment and navigate to known objects.

Description of the vehicle

The small mobile robot employed in this paper, named Gator [7], is constructed from LEGO building blocks. Gator measures 27 cm long, 12 cm wide, and 20 cm tall. It is powered by six AA NiCd batteries and can run for approximately 45 minutes on a charge. Gator is controlled by one MC68HC11 microcontroller and uses less than 2 Kbytes of code to accomplish its tasks. Two bi-directional DC motors drive, respectively, the left and right tracks of the robot, which travels about 105 mm/s at top speed. Gator also possesses a 2-DOF arm capable of grasping small objects and lifting them 7 cm above the ground. An IR detector in Gator's gripper detects the presence or absence of a marker. Actuator stop switches prevent overdriving the joints. This 2-DOF manipulator permits Gator to pick-and-place a portable marker to assist in landmark map construction.

Gator possesses a variety of sensors. The left and right sides of Gator support two IR proximity detectors which provide the requisite information for following a wall on either the left or the right of the robot. Three forward looking IR proximity detectors provide the function of object detection and collision avoidance. The IR detectors are "near-sighted" with a range of about 200 mm. The shaft encoders on the wheels record every quarter turn of the wheel. One shaft-encoder tick translates into about 34 mm of linear motion.

Innate behaviors

Basic capabilities of the vehicle directly relying on its hardware structure and sensor suite are the following:

- `obstacle-detection`: an obstacle-landmark is detected by means of the front IR sensors;
- `random-wandering`: the robot takes a random direction after detecting an obstacle;
- `wall-following`: the robot mantains the obstacle at a fixed distance (at its left or right) by alternating between two levels of IR sensitivity;
- `align-with-wall`: initial alignment with the object before proceeding with exploration;
- `turn-around-180`: manouvre to back up and turn 180^o;
- `drop-marker, detect-marker, pickup-marker`: marker manipulation.

More complex capabilities built upon the previous ones are:

- `obstacle-contouring`: uses `wall-following`, `turn-around-180` and marker manipulation;
- `corner-detection`: during `obstacle-contouring` the robot detects a corner by perceiving a sequence of steering corrections in the same direction during a specified time frame; the center of the steering command window estimates the corner location; in *left* `wall-following`, a corner detected with steering corrections to the right is a *concave* corner, while steering corrections to the left imply a *convex* corner; no attempt is made to integrate the turning commands over time to estimate the angle, which cannot be done with any reliability;
- `object-features-measurement`: is based on `obstacle-contouring` and `corner-detection`, and on gross odometric measurements of the traveled distances.

We collectively term the above capabilities of the vehicle as *innate behaviors*. These behaviors have been implemented and experimentally verified on Gator. They provide the basic sensorimotor procedures exploited in map construction and navigation.

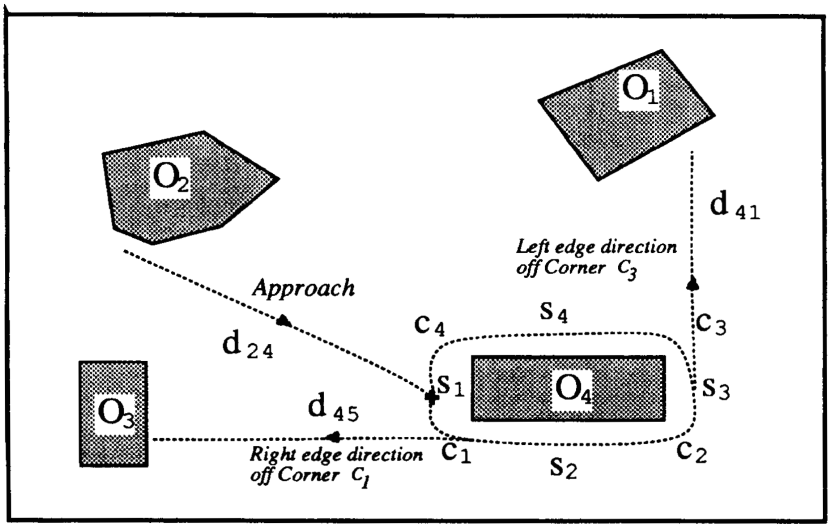

Figure 1: Constructing a map in an enclosed environment.

THE MAPPING ALGORITHM

The "closed door" assumption

The operational environment of the robot is assumed to be an enclosed, level space populated by polygonal objects with walls along each side (Figure 1). Due to sensor limitations, non-polygonal objects in the environment will be either erroneously catalogued by the robot as polygonal landmarks or as ill-defined landmarks. Ill-defined landmarks will be so designated in the landmark map and will simply be avoided in path planning.

We also assume that the robot always meets objects at one of their sides, as shown in Figure 1. This assumption is easily verified in practice, since corners cannot be immediately identified. The robot always attempts to align with the object as its first operation after object detection.

Landmark map data structure

Based on the innate behaviors previously discussed, each polygonal landmark is described by a data structure containing topological as well as metric information accounting for side labeling, approximate side lengths, corner labeling, corner type (convex or concave), corner to side relationships. A typical landmark data structure is outlined in Figure 2. Since landmarks are initially contoured according to the right hand rule, all descriptions of a given object will match (approximately), up to a rotation of the elements in the data structure.

In the basic mapping algorithm, when leaving an object the robot always takes an *edge direction* heading at a corner point (Figure 1). Each corner has a left and a right edge direction, hence an n-sided object has 2n potential edge directions.

A landmark map consists of a weighted directed graph of objects (landmark) nodes (Figure 3). Edge weights equal measured distances between objects represented by the nodes the edge connects. Exit edges from a node must be rooted in a corner edge direction and edges incident to a node must be at a side label. This edge incidence structure at a node reflects the fact that the robot

1. detects and approaches walls or sides of objects and aligns with same before contouring and measuring an object,
2. always leaves an object from a corner in an edge direction.

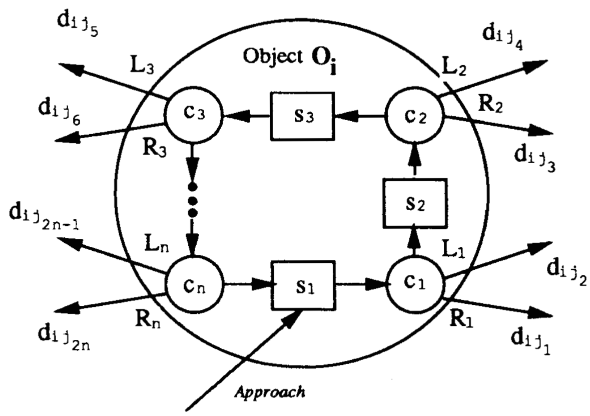

Figure 2: Internal representation of an n-sided landmark.

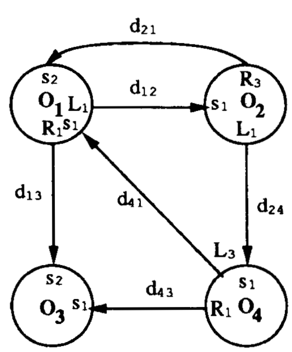

Figure 3: Example of a landmark-based map data structure.

Map construction

The autonomous map building process begins with the robot executing **random-wandering** while carrying a single, portable marker in its gripper. Upon detecting an object it executes **object-features-measurement** and generates an object node structure. The robot compares the generated landmark with others in its map data base. If no match occurs, the robot enters the object as a new landmark whose side S_1 corresponds to the incident side (refer to Figure 1). The robot then takes an edge direction from a corner and travels in a straight line until it detects the next object. The recorded distance to the next object supplements the topological information and provides disambiguation information for objects with the same perceived features.

If the object matches one already in the current map, the robot can determine the label of the incident side, provided the object has no perceived symmetries. If the label of the incident side can be determined, the robot picks an untried edge direction at one of the objects corners and proceeds. This will enhance the map coverage.

On the other hand, if the label of the incident side cannot be uniquely determined, the robot arbitrarily hypothesizes a side, moves to the nearest corner, and departs the object in an edge direction that has been previously traversed. Based on the hypothesis, traversing that edge direction should lead to a known object at a known distance. If the expected events happen, the hypothesis was correct and the robot knows where it is. Otherwise, the robot attempts disambiguation by referring back to the original node to determine if the data matches some other exit edge. If not, the robot could be programmed to remember up to n previous landmark visitations for disambiguation analysis. We opine that $n = 2$ will be a good compromise between computational complexity and map building efficiency.

The mapping algorithm is not necessarily carried out until all edges have been explored. In fact, a map does not need to be complete to be useful. A possible terminating condition could be the existence of a path connecting all found landmarks.

Discussion

The above mapping algorithm is exposed to three basic problems. Non-cornered objects do not determine any self-relative edge directions, thus specific headings from such objects will be random and unknown. If such an object is met, the robot will recognize it as ill-defined, label it as such in the map, leave the object from an unknown direction, and continue the mapping algorithm with whatever object it encounters next. Multiple symmetries would be another source of problem, but they are seldom an issue in practice.

A more substantial problem arises when the objects cannot be reached from one another from any edge direction, owing to the sparsity of the environment. To overcome this problem, the mapping algorithm is followed by a random exploration phase. In order to relate otherwise isolated landmarks, the vehicle must possess the capability of departing from the objects at a side with a 90^o turn, keeping also track of the departing point along the side. However, this and other topics relating to derived information from the raw sensor data will be addressed in future work.

MAP ASSISTED NAVIGATION

We approach navigation with a landmark map in the spirit of [1] and [11]. The map provides information for the robot motion behaviors, not inflexible commands. When the robot is asked to navigate to a landmark in its current map, the robot first locates itself. Next, it plots a trajectory to the target landmark based upon the map information. However, due to unexpected obstacles or poor sensor performance the robot may find itself lost. In such cases, or if no path could be planned on the map, the robot will wander about until it recognizes a known landmark. It will then formulate and execute a new plan from the current landmark.

EXPERIMENTS

At this time Gator can perform a slightly modified (to increase reliability) landmark measurement behavior. Instead of picking up the marker when the grasp detector indicates its presence, the robot stops, backs up a few centimeters, turns 180^o, and executes right contouring until the marker is encountered once again. The robot then stops and the behavior terminates. Object side lengths are averaged over the two contouring operations. Our successful implementation of the modified landmark measurement behavior verifies that Gator possesses the ability to perform landmark map construction and navigation.

In the experiments, Gator was placed in a 10 foot by 10 foot arena containing white-cardboard, rectangular obstacles. A number of contouring experiments were performed, also verifying convex and concave corner detection capabilities. A dry erase marker attached in the back of Gator traced out on a tile floor the contours generated by the modified **object-features-measurement** behavior. For example, Figure 4 illustrates a double-contour about a rectangular object, with one trace generated by *left* contouring and the other by *right* contouring. By analyzing the traces left by Gator along several experiments, we have found that multiple contouring of the same object exhibits good path repeatability and that perimeters are measured consistently within a 15% range.

The full map construction and navigation algorithms have not been run on Gator so far, owing to the limited amount of memory currently on-board. While hardware improvements on Gator are underway, we have developed a PC-based simulated environment for testing of the algorithms (Figure 5). In the simulation we have attempted to reproduce the limited sensorimotor abilities of the physical vehicle, along with the adopted control strategies. The simulated experiments have suggested a slight modification of the mapping algorithm to better take advantage of the localizing information provided by corners at the enclosure. An enclosure wall is immediately identified when a prolonged **wall-following** behavior occurs. In this case, when a corner is met the robot departs from the enclosure toward the interior space. If the corner is concave the robot takes a direction approximately along the bisector by equalizing the readings of the lateral sensors, while if the corner is convex the robot follows the current edge direction.

An example of a simulated run of the mapping algorithm is shown in Figure 5. The white circle represents the robot's current location, while the black dots, shown for ease of interpretation, represent locations where marker was dropped during **obstacle-contouring**. The simulated robot started at the top left of the operational environment and successfully identified the three landmark-objects, along with features of the enclosure. While the simulation experiments show a potential validity of the approach, further experimental verification on physical vehicles is undoubtfully needed and currently pursued.

CONCLUSION

The proposed landmark mapping and navigation scheme exploiting "near-sighted" sensors and imprecise odometry appears feasible, based upon our partial implementation. We have demonstrated the fundamental requirement of landmark measurement experimentally; experimental landmark map construction and navigation awaits further development, but encouraging results have been obtained in simulation.

Of course, the resulting maps will be often incomplete, and sometimes inadequate to support goal-oriented navigation. Path optimality is also ignored in the approach. However, robustness and improvement over a random search navigation are more appropriate goals, given the limited information available in a large-scale space of very sparse landmarks.

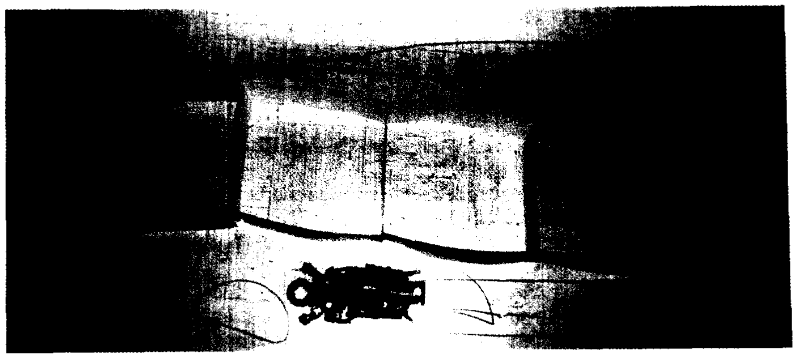

Figure 4: Gator measuring the features of a rectangular landmark. The robot is picking up the marker at the end of the second contouring operation.

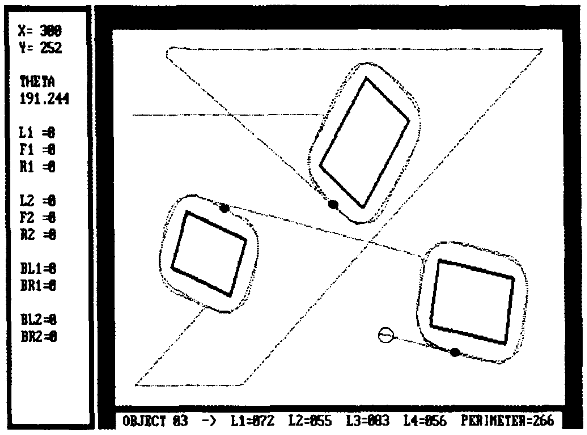

Figure 5: Simulation run of the mapping algorithm.

Acknowledgment

The authors wish to thank A. Calafiore and D. Diemmi for their contribution to the development of the simulation.

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