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Organized by the European Coordinating Committee for Artificial Intelligence (ECCAI)
Hosted by the Universities of Brighton and Sussex on behalf of the Society for the Study of Artificial Intelligence and the Simulation of Behaviour (AISB)

Proceedings

Edited by
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Possibility theory-based environment modelling by means of behaviour-based autonomous robots

Maite López-Sánchez, Ramon López de Mántaras, and Carles Sierra

Abstract. In this paper we present the results obtained so far with a troupe of low-cost robots designed to cooperatively explore and acquire the map of unknown structured orthogonal environments. The returning robots deliver to a host computer the partial maps they have built and the host generates the most plausible global map. Maps are represented as a possibility/necessity grid. In order to increase the coverage of the map, the host analyses the detected walls and obstacles and generates paths to send robots to non explored areas. Each robot navigates using behaviour-based strategies that result in two main global behaviours: random exploration and path following. When two robots meet they cooperate by communicating their partial maps.

1 INTRODUCTION

Brooks [2] behaviour-based approaches have proved to be a good way of coping with the complexity of architectures for navigation because they decompose the problem into small and independent decision-making processes (called behaviours). We are using this behaviour-based approach to develop a troupe of low-cost small autonomous robots following the already classical line of insect robots. The goal of these autonomous robots is to explore and obtain information about an orthogonal environment, unknown and easily passable, and deliver this information to a host computer.

Initially robots disperse through the environment looking for walls and obstacles. Exploration is performed moving randomly in free space and following walls (or obstacle edges) when detected. Afterwards, if during exploration two of them meet, they share their information about detected objects. Sharing information when meeting allows the host to get the information not only from the robots that successfully return after an exploratory run, but also some information from those that, after encountering successfully returning robots, could not return. Finally, after returning they deliver information about the position of objects to the host. Then, the computer host generates the most plausible map from the information obtained by the returning robots. This map models the environment in terms of degrees of possibility and necessity of the position of the detected walls and obstacles. This uncertainty is due to the odometry error that robots accumulate along their runs.

The troupe of small low-cost robots implements a distributed solution to the exploration problem and allows to increase the coverage of the environment with respect to what would be obtained using a single expensive robot. Robots have been designed having in mind that the hardware had to be as simple as possible but, on the other hand, it had to show a smart behaviour in order to navigate efficiently. These requirements resulted in a design which contains three different functional modules: the steering module that controls the motors in order to follow a trajectory; the perception module that acquires information of the environment by means of IR sensors; and the navigation module that generates the trajectory to be followed (see [6] for details). Each robot is equipped with the following sensors:

-Impulse generators at each wheel for odometry,
- Five I.R. proximity sensors for obstacles detection placed at 0°, ±45° and ± 90°. These provide two possible readings: 'near' and 'far' which correspond to 10 and 20 cm respectively.
- Safety micro switches to detect collisions.
- Omnidirectional IR Receiver/Emitter sensor that detects the presence of other robots and transmits data.

Section three gives a detailed description of their global strategies (random exploration and path following). Then, we describe a statistical error analysis performed in order to know how the error intervals increase with respect to distance and number of turns. This analysis will be used to model the environment using the notions of possibility and necessity. The fifth section describes the combination of partial maps obtained by successfully returning robots. Finally, we describe the results of a simulation of the troupe, we briefly point to related work and we mention some future work.

2 BEHAVIOUR-BASED STRATEGIES

Each robot implements two navigation strategies (random exploration and path following) that are based on the co-ordination among different elementary behaviours. Basically, our architecture is a deterministic finite state automata in which each state corresponds to an elementary behaviour. Figure 1 shows the automata of the random exploration. The automata corresponding to the path following strategy is similar.

These basic behaviours use sensor readings as well as historical information of previously taken decisions to determine what are the actions to execute and when to switch to other behaviours under the conditions shown as labels in the arcs in Figure 1. This 'one behaviour active at a time' policy avoids the problem of combination of outcomes that appears in those approaches activating more than one simple behaviour simultaneously [10].

The control is done by means of a loop that has tree stages: sensor reading, local planning and action execution. The reactive-deliberative module has two sets of If-Then rules: reactive and deliberative rules. The former have a higher priority and are fired for specific sensor readings (as for example, collision detection) to force the module to react quickly with predetermined actions. Nevertheless, in the absence of such readings, deliberative rules (which also consider historical information) are fired. Every behaviour has a goal and has knowledge in the deliberative rules to

• Artificial Intelligence Research Institute,
IIIA Spanish Scientific Research Council, CSIC
Campus UAB, 08193 Bellaterra, Spain
{maite, mantaras, sierra}@iiia.csic.es

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sensor, stops and waits for the same frequency in the received signal from the partner to switch into the data transmission behaviour.

2.3 Navigation Performance

At the bottom level, the navigation is nothing more than a sequence of actions (turn, move, stop) executed in the environment. These actions are commands to the effectors.

The sequence of actions is generated by the currently active elementary behaviour, which sets the sub-goal that must be executed and controls its success, interruption or adaptation. For example, when a wall-following elementary behaviour is active it sets a sub-goal (a displacement of a certain length and orientation) and controls its execution using sensors: wheel encoders give the travelled distance (this is the clue for the sub-goal success), any front detection cancels the behaviour and too far or too close side sensor readings indicate that the orientation must be adjusted by means of a reactive re-planning.

In switching between elementary behaviours, the history of previous decisions helps in the selection of new behaviours.

3 ERROR ANALYSIS

With the aim of studying the error in the assessment of the exact position of each robot due to the imprecise odometry and to the imprecise steering, we have performed an analysis of experimental data obtained from a real robot running straight (10 feet and 20 feet). We have performed 20 trials of each run and turning situation. With the data obtained, we have used the Kolmogorov normality test to verify that the experimental sample indeed follows a normal distribution both in the direction of the trajectory and in the direction perpendicular to the trajectory and we have tested that both distributions are independent. Based on these distributions we have determined the size of an error rectangle, comprising the 95% of the sample (which is elliptically shaped), associated to the final position of the robot after a straight run of 10 feet. This rectangle is 2.5 inches (in the direction of the trajectory) x 11 inches (in the direction perpendicular to the trajectory) in the average. We have also experimentally concluded that the size of the error rectangle is proportional to the covered distance.

In free space, a trajectory is composed of a set of segments separated by turns. Given the error rectangle at the initial point of a segment, is easy to determine the error rectangle at its end taking into account the error accumulated along it. see [5] for details.

This error analysis and error propagation study should be performed for each different robot and is used by the host to compute the possibility/necessity grid modelling the environment as described in the next section.

4 MAP GENERATION

The space being explored by the robots is discretised by means of a grid. Cells in the grid represent a small area of the real environment and contain two values: the degree of possibility and the degree of necessity of the presence of obstacles. Initially, that is, before any exploration has taken place, each cell, represented by its co-ordinates (x_i, y_j), has a possibility value $\Pi_{ij}(\text{wall})=1$ (i.e., it is completely possible that there is a wall or obstacle in the cell) and a necessity value $N_{ij}(\text{wall})=0$ (i.e., there is no certainty at all that there is a wall or obstacle in the cell). These initial values correspond to a situation of total ignorance according to the theory of possibility [3]. As robots communicate the information gathered during their exploration to the host, the possibility and necessity values are modified in a way that depends on the detection, or not, of obstacles by the returning robot. The information gathered by each robot is the trajectory of the robot together with the position of the walls and singular points (that is wall ends and corners) that have been detected along it. Due to the odometry error, the position of the detected walls has an associated error. As we have explained in the last section, we have experimentally determined this error which has been approximated by a rectangle centred around the cell corresponding to the estimated position of the robot.

The reason for choosing possibility/necessity techniques instead of probability is the need for an initial assignment of values representing ignorance. Possibility theory allows a clear representation of ignorance but probability does not because, for example, initialising each cell with a probability value of 0.5, as it is usually done, does not reflect ignorance, on the contrary it assumes in fact quite a lot of knowledge, namely that the discretized environment has as many empty cells as occupied ones.

4.1 Modelling uncertainty

When an error rectangle is associated to a position that belongs to a detected wall, the occupancy certainty degree (that is the certainty about the presence of an obstacle in that position) is expressed by means of necessity values in every cell that results partially or totally covered by the error rectangle around that position. The necessity values decrease linearly (from the center of the error rectangle) with the magnitude of the error and remains positive ($N_{ij}(\text{wall}) > 0$) for all the cells inside the error rectangle but gets the value 0 at the cells outside the limits of the rectangle. These values have been established with the aim of reflecting that, having detected some obstacle, the necessity that there is a wall cannot be longer zero but positive since a positive value denotes some certainty degree about the occupancy of the space. However this occupancy certainty degree decreases when the distance to the central cell of the error rectangle increases. Figure 3 a) shows this case. Notice that according to the axioms of possibility theory, the possibility value is constantly equal to 1 in all the cells covered by the error rectangle.

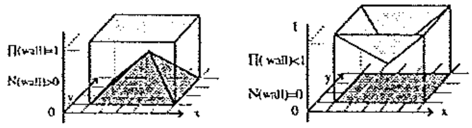

Figure 3: Π and N values assigned to cells corresponding to : a) wall detection, and b) free space.

We distinguish singular points (i.e. wall endings) from the rest of occupied cells in the map representation. This is done by means of an extra label so that possibility and necessity assignments remain the same.

On the other hand, paths along grid cells in which there was no detection supply information of free space, that is in these cells $\Pi_{ij}(\neg\text{wall})=1$ and $N_{ij}(\neg\text{wall})>0$, or equivalently, according to the axioms of possibility theory, $N_{ij}(\text{wall})=0$ and $\Pi_{ij}(\text{wall})<1$. This possibility value increases linearly with the distance to the central cell of the error rectangle until it reaches the value 1 at the cells outside the limits of the error rectangle. Obviously, according to or obstacles by red and singular points by green. The darker the blue along the four trajectories, the smaller the possibility value Π(wall). For the detected wall segments, the lighter the red the smaller the certainty value N(wall). The green degradation in the singular points also reflects the decrease of certainty about their actual position.

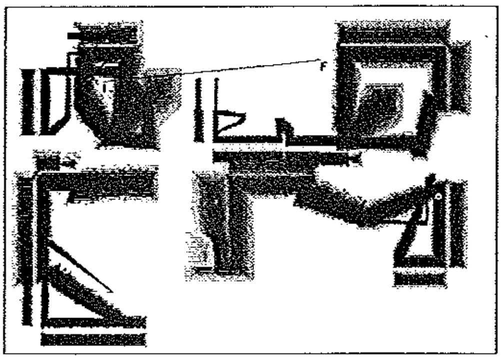

Figure 7: Global map obtained from four partial maps. The line between 'I' and 'F' is a planned path

The user can then ask the host to compute the path between any two selected positions (for instance, those labelled 'I' and 'F' to represent the Initial and Final points). The generated path between T and F is shown in the Figure 7 as a straight segment between them. As we can see, it is coherent with the available information. However, when information is incomplete, the resulting path can be difficult to follow. In our case, for example, the proposed path goes through a real wall. Figure 8 shows how a robot uses this path and reacts in front of unexpected walls.

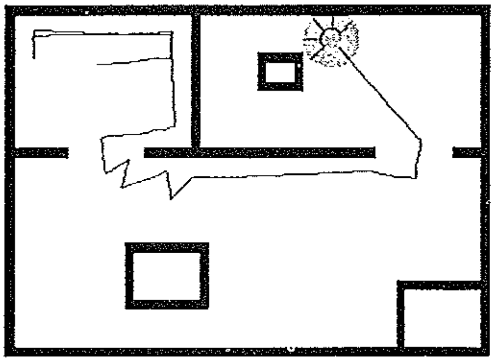

Figure 8: A robot follows the path from figure 13.

7 RELATED WORK

Two main characteristics differentiate our work from others addressing the problem of map building: the type of sensors that are used and the techniques that are applied for map representation.

Concerning map representation, the use of probabilistic techniques is quite common, for example [1] defines landmarks in natural environments assuming a Gaussian certainty distribution of their positions and [7] estimate the probability of cell occupancy in certainty grid representations. Probabilistic techniques need a huge amount of data and assume known distributions, Fuzzy Set theory is a good alternative when these conditions are not met [4, 8].

The submitted version included additional references, but due to space limitations they could not be included in its submitted form. Interested readers can access the long version of this paper as a research report at http://www.iiia.csic.es.

8 CONCLUSIONS AND FURTHER WORK

We have presented a map representation grid-based method that is in fact an alternative to a previous work [6]. This new method is based on a local computation of possibility and necessity values, and takes advantage of the fact that possibility and necessity are dual measures and, furthermore, is computationally simple. We are now in the process of incorporating this new approach to the real robots being presently built at the Control Engineering department of the Technical University of Barcelona under the supervision of Prof. Josep Amat.

An alternative approach worth considering to model uncertainty would be to use probability intervals instead of single probability values. Also, in the approach we have used it would be interesting to make an empirical comparison of different combination functions. These are left for further work.

As additional further work we plan to improve the deliberative sub-module of each elementary behaviour. First, it is possible to improve navigation strategies developing in this module a clever supervision of the history. We will address, as well, the problem of learning higher level environment concepts as "corner", "door", etc. That is, we will address the problem of symbol grounding by a case-based learning process based on sequences of sensor readings.

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