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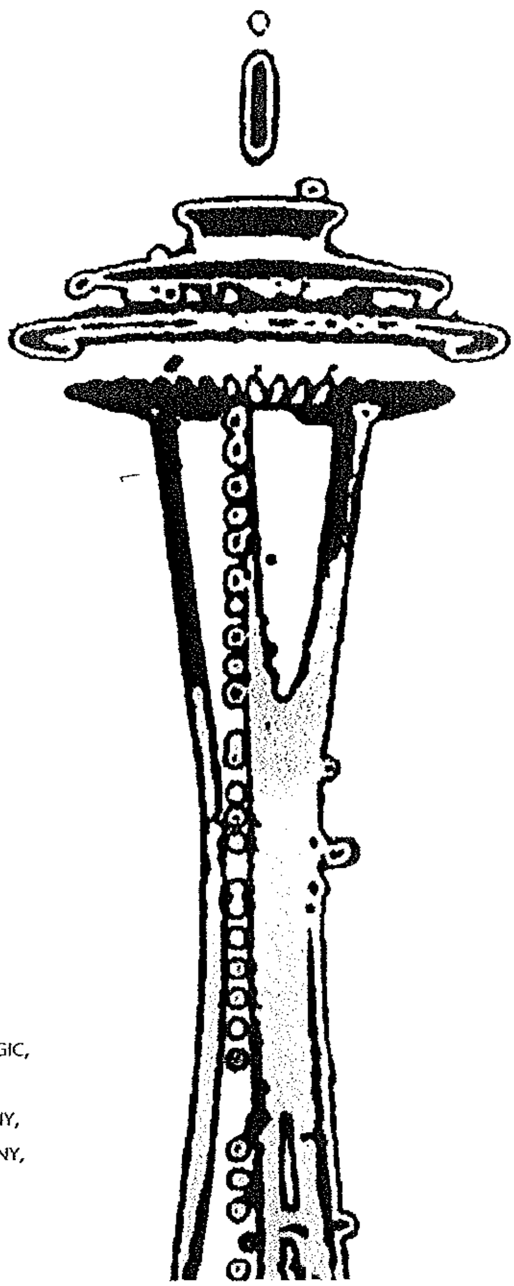

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Map Generation by means of Autonomous Robots and Possibility Propagation Techniques

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Abstract

We use a behaviour-based approach to develop a troupe of low-cost autonomous robots that explore structured indoor environments. Robots explore by moving randomly in free space and following walls and obstacles when detected. Robots share their information when they meet. This allows a host computer to map the environment based on the information coming not only from the robots that successfully return but also from those that failed to return but have met one of the returning robots. The map is a grid representation having uncertainty occupancy values for each cell. Uncertainty values are due to robot errors and are represented by possibility Π and necessity $\mathcal{N}$ values. We present a method that propagates and combines Π and $\mathcal{N}$ values locally. It is a computationally simpler alternative to a previous work [3] and takes advantage of the fact that Π and $\mathcal{N}$ are dual measures. We also introduce a method to extend the detected walls in order to plan safer paths over generated maps. Robots can use these paths to reach less explored areas.

1 Behaviour-Based Navigation

We use a behaviour-based approach [1] to implement two navigation strategies for our robots: exploration and path following. These strategies are based on the co-ordination among different elementary behaviours. Each behaviour corresponds to a state in a deterministic finite state automata (see Fig. 1) and use sensor readings (shown as labels in the arcs) to switch the control between behaviours. The random exploration strategy co-ordinates elementary behaviours to cover free space by changing the robot's direction randomly and by following segments of walls (or obstacle edges) when detected. The path-following is a very similar strategy that reacts upon unexpected obstacles while following a given path. Both strategies share two more behaviours concerning communication: presence detection and data transmission (they are not shown in the figure due to the lack of space).

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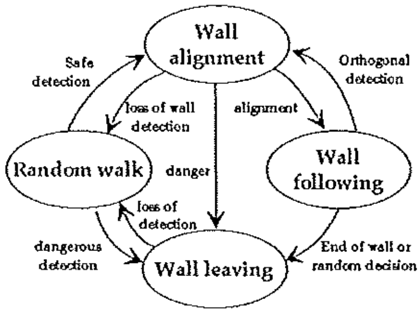

Figure 1: Automata schema of the random exploration strategy (*Random Walk* becomes *Directed Walk* in the path following strategy).

2 Map Generation

The explored space is represented by means of a grid. Grid cells contain two degree values: the possibility and necessity of the presence of obstacles. Initially, every cell has a possibility value $\Pi_{ij}(wall) = 1$ and a necessity value $N_{ij}(wall) = 0$ (being (i, j) its position). When the host receives robots' information, it associates an increasing error rectangle (studied in [2]) to every estimated position of robots and walls. Wall detections give occupancy values of $N_{ij}(wall) > 0$ in cells covered by the error rectangles associated to detected positions (these values decrease linearly with the error). On the other hand, paths along grid cells supply information of free space ($N_{ij}(\neg wall) > 0$). According to possibility theory, possibility values $\Pi_{ij}(wall) < 1$ are computed using $\Pi_{ij}(wall) = 1 - N_{ij}(\neg wall) > 0$ (and increase linearly towards 1). Necessity values are computed as follows: At time t, we compute the height of the central cell of an error rectangle defined by e_x, e_y:

$$n_{i,j}^t(wall) = 1 - \frac{max(e_x, e_y)}{K}$$

Next, the propagation of this measure $n_{i,j}^t$ around this central cell follows these inequations :

$$n_{n-1,m}^t(wall) \geq n_{n,m}^t(wall) \cdot max(0, 1 - \frac{|(n-1)-i|}{e_y})$$

$$n_{n+1,m}^t(wall) \geq n_{n,m}^t(wall) \cdot max(0, 1 - \frac{|(n+1)-i|}{e_y})$$

$$n_{n,m-1}^t(wall) \geq n_{n,m}^t(wall) \cdot max(0, 1 - \frac{|(m-1)-j|}{e_x})$$

$$n_{n,m+1}^t(wall) \geq n_{n,m}^t(wall) \cdot max(0, 1 - \frac{|(m+1)-j|}{e_x})$$

The final value we assign to a cell is the minimum value that satisfies all inequations. A cell will neither take nor propagate a value received if it is smaller than the maximum of previously received values (convergence).

Finally, the necessity N is updated as follows:

$$N_{n,m}^t(wall) = max(N_{n,m}^{t-1}, n_{n,m}^t(wall))$$

The values $N_{n,m}^t(\neg wall)$ are computed in a similar way.

2.1 Map treatment

In order to increase the number of different detected walls or obstacle edges, robots leave walls before reaching their ends. Therefore, wall segments without singular points (detected ends) correspond to longer walls —or obstacle edges. The host extends these segments until they reach a robot trajectory or another segment. Extension is done locally over orthogonal segments by propagating low constant certainty values of occupation. In this manner, extension increases the coverage of the environment. Moreover, planning (using a visibility graph) over extended maps gives long but safe paths that require less reactivity in front of unexpected obstacles.

3 Results

Figure 2 (up) depicts the trajectories of four robots exploring a simulated environment. The detected map (45.3% of coverage) is included in the extended map in the middle; the difference is the segment extensions in light grey (70.1% correct coverage and 6.4% incorrectly expanded). The same initial and final points yields to different planned paths. Down, the figure shows robots' trajectories when following these paths.

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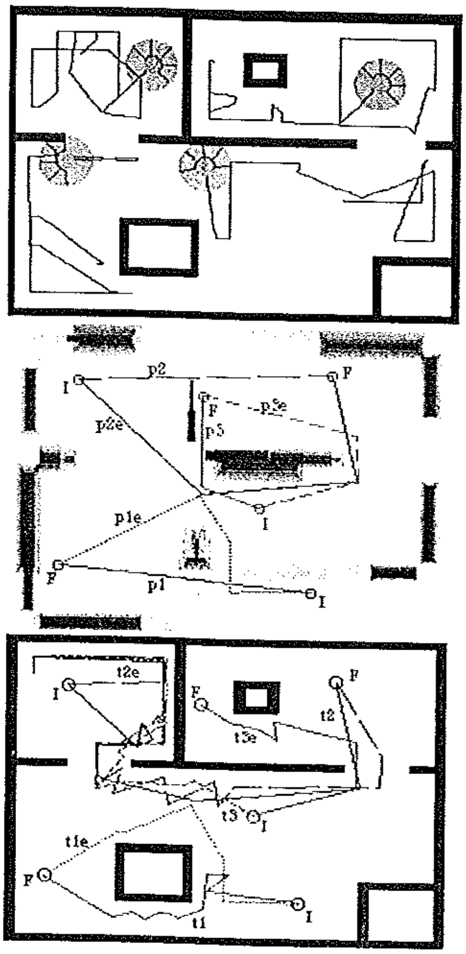

Figure 2: Up: Exploration of four robots. Middle: Extended map (extension in light grey). Paths p1, p2 and p3 do not consider the segment extensions, paths p1e, p2e and p3e do consider them. Down: Performance of the robots following the obtained paths(Reactivity is not enough for t3 to reach the final position, the robot stops before due to the accumulated error).

References

[1] R. Brooks: Intelligence Without Reason. Proc. International Joint Conference on Artificial Intelligence, 1991 pp.569–595

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