Planning sensor-based motions for mobile robot navigation

Thierry Simeon, Rachid Alami

Planning sensor-based motions for mobile robot navigation

T. Siméon and R. Alami

LAAS-CNRS
7, avenue du Colonel-Roche
31077 Toulouse Cedex - France

Abstract: *Motion planning and control are two important aspects for mobile robot navigation. They are often considered as two separate phases, leading to a lack of robustness when experimented in real world settings. The objective of the presented approach is to bridge the gap between motion planning and motion control. Motion planning is performed in terms of closed-loop sensor-based primitives rather than in terms of a geometric path whose execution is more sensitive to perception and motion uncertainties. Experiments performed with the* Hilare2 *mobile robot show the effectiveness of the algorithms for achieving robust navigation in* a priori *known indoors environments.*

1 Introduction

Motion planning and control are two important aspects required for mobile robot autonomous navigation. However, they are frequently considered as two separate phases. Many motion planning techniques have been proposed to produce a collision-free and feasible path avoiding the obstacles of the workspace (see [6] for a survey). Motion control then consists in making the robot follow this path, possibly using a potential-field based method [4, 5] for reacting to unexpected obstacles sensed during the execution. Such decoupled approach suffers from a lack of robustness when experimented in real world settings since the execution of the planned trajectory is conditioned by several sources of uncertainties.

Control and sensing errors are particularly significant in the context of mobile robot navigation. Indeed, mobile robots are not generally equipped with an absolute positioning system and are subject to cumulative dead-reckoning errors. Such inaccuracies in localizing the robot with respect to its environment may lead to execution failures. To overcome the uncertainty accumulated during the motions, the robot can be equipped with environment sensors that provide additional information by identifying appropriate features of the workspace. Localization techniques (e.g. [2, 8]) can be applied to reduce the uncertainty of the estimated configuration. One may also use sensor-based motion commands which are more tolerant to errors than classical position-controlled commands. Sensor-based control generally considers the development of specific primitives (e.g., wall-following using ultrasonic sensors [10] or vision [13]), without connection with a planning component. In situations where much is known in advance on the environment, it may be preferable to combine such sensor-based commands with a planning component reasonning onto the uncertainty possibly accumulated during the motions and onto the capacities of the available sensing functions. Such component may allow to use the available knowledge to produce robust motions plans that will reliably guide the robot towards its goal.

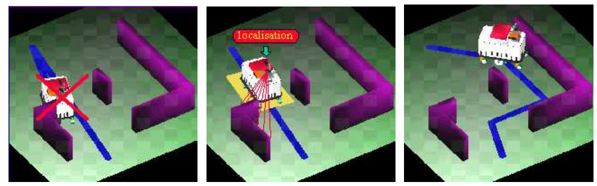


Figure 1: Motion plans using odometry based commands **(a)**, landmark localizations **(b)** and wall-following commands **(c)**

The paper illustrates this approach with the algorithms that have been developped and integrated onto the `Hilare2` mobile robot for achieving robust navigation in an a priori known office-like environment [11]. The robustness comes from the link between a planning component [1] reasoning onto uncertainties and sensor-based motion control [10].

2 Motion primitives

We first introduce the several types of motion primitives that are considered both at planning and execution level:

- **Free space motions:** the *move* primitives correspond to classical position-controlled commands using odometry. The position error is defined as a function of the distance covered by the robot.

The *move_landmark* primitive is controlled by the measure provided by an external sensor (eg. camera) which allows to maintain the position error to the sensor accuracy.

- **Guarded motions:** *move_to_contact* executes a straight line motion stopped when an obstacle is detected. This allows to reset the position error along the direction orthogonal to the edge. A *parallelize* primitive can then be used to align the robot with a wall.
- **Sensor-based motions:** *wall_follow* is a composed sensor-based command for following a succession of walls. Several events (corner detection, traveled distance...) are checked during its execution. This primitive only accumulates error in the direction of the followed wall because of the use of the odometric sensor to determine the covered distance. However, this error can be reduced when corners are detected during the wall following.

3 Robust motion strategies

Given a model of the uncertainty accumulated by the motion primitives defined above, we consider the problem of computing a motion strategy composed by a sequence of such primitives. A robust motion strategy should guarantee that the robot, starting from an uncertain initial position, can reliably reach its goal with an error lower than a pre-specified value, despite the errors accumulated by the motion commands. It should also contain the corrective sensor-based motions needed to reduce the error (e.g. by entering in landmark regions or by detecting some walls or corners in the environment).

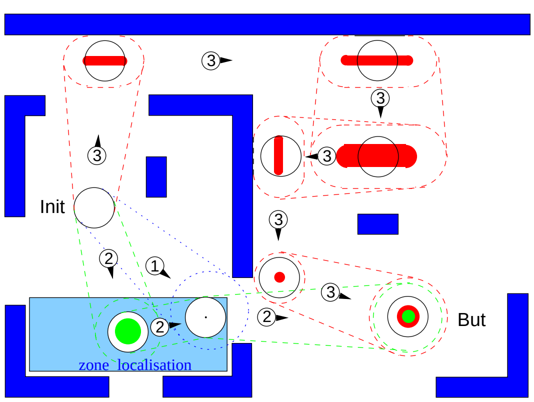


Figure 2: Example of motion strategies

Figure 2 shows the uncertainty evolution for different motion strategies that may be used to solve the same planning problem. Free space motions (strategy 1) would not allow in this example to connect the "Init" and "Goal" positions since the accumulated error would be too important to safely pass the doorway. Strategy 2 solves the problem by traversing a landmark region (within which the uncertainty remains bounded) whereas strategy 3 illustrates the evolution of uncertainty using wall-following motions.

We proposed several algorithms for solving different instances of such problem (related problems were also adressed in several other works -e.g. [15, 7, 9, 12]). The algorithm [14] produces a sequence of *follow-wall* commands, based onto an analytic computation of *reachability regions* in the parameter space of these commands. The landmark-based planner [3] developped in the context of outdoors navigation takes into account possible error reduction by introducing *move-landmark* commands inside the motion plan. The planning algorithm [1] described below and that was integrated onto our `Hilare2` robot offers more powerfull capabilities: it is able , whenever possible to navigate without localizing the robot when the task does not impose it (free-space motions may be faster than following a wall), and also allows to combine *wall-follow* and *move-landmark* commands for error reduction.

4 Planning algorithm

The planner [1] considers a polygonal description of the obstacles and also a set of landmark regions where the robot can be relocalized in the environment. The algorithm is based on the propagation of a numerical potential modeling the uncertainty evolution and on a geometric analysis of the reachability of environments features (walls or landmark regions).

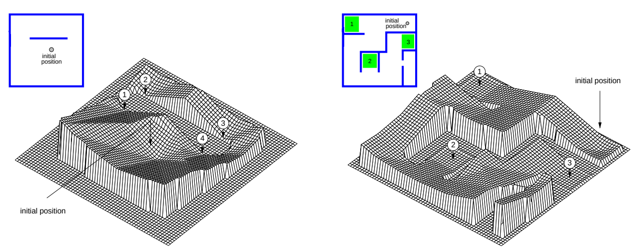


Figure 3: Numerical potential with possible error reduction by following a wall (a) or entering in landmark regions (b)

During the propagation of the potential, collisions are checked between the obstacles and the robot shape grown by the current uncertainty. The robot is approximated by its enclosing disk during the free-space motions. The exact shape is only considered during the wall-following commands for which the robot has to be aligned with the wall. This allows to solve constrained problems (eg. crossing of narrow doorways) where the circular approximation would be too conservative, while only considering a two-dimensional configuration space.

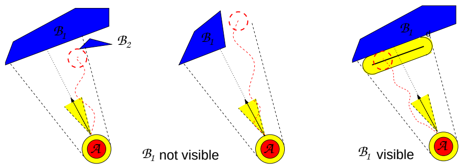


Figure 4: Visibility test for guarded motions

When the propagation reaches a position which may collide with a given edge because of a too large uncertainty, a geometric visibility test is performed to check if a *guarded motion* is guaranteed to end onto this edge (Fig. 4). When this test succeeds, the algorithm starts from this position a propagation adapted to the uncertainty model of the *wall_follow* commands (Fig. 3-a). Similarly, a propagation adapted to the *move_landmark* command is started at positions where the robot grown by its current uncertainty is included in a landmark region (Fig. 3-b).

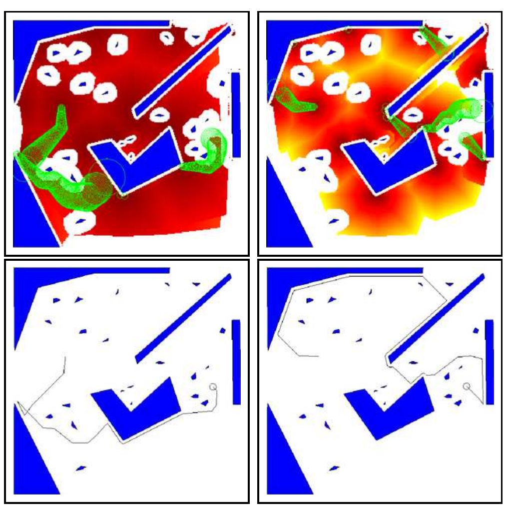


Figure 5: Examples of computed strategies

Finally, once the goal position is reached with an admissible uncertainty, the motion plan is deduced by backchaining configurations from the goal to the initial position. The strategies returned by the planner either minimize the distance crossed by the robot (see Fig. 5-left, ignoring in this case relocalizations when the task does not impose it) or the final uncertainty (Fig. 5-right).

5 Experimentations

This section illustrates some of the experiments that have been performed in our laboratory to demonstrate the robustness of the approach. The `Hilare2` mobile robot is equipped with a belt of 32 sonars and a laser range finder. Sonar data are used for the *wall-follow*, *move to contact* and *parallelize* actions. The laser is used for edge detection and corner matching during a wall-following.

The sensor-based motion primitives are defined at the execution level by specific functions called *Task-Potential* functions [10, 11]. The task potential is a non convex potential function that allows to express a sensor-based action in a space parametrized in terms of the sensor output variables. The execution of the task corresponds to a gradient descent of a global potential composed linearly from several elementary potential functions.

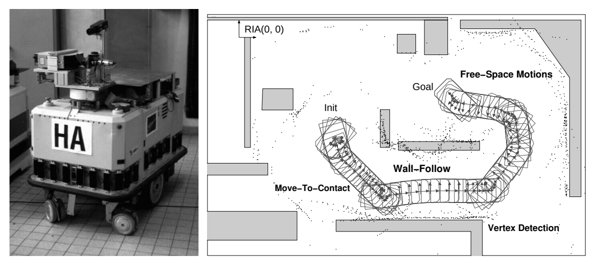


Figure 6: Experiment 1

Figure 6 shows the trace of the motion plan executed by `Hilare2` during one of the experiments. Given the rough estimate of the initial position, the goal is not reachable using a direct open-loop free-space motion. The planner strategy was to generate several sensor-based actions (move to contact, follow wall until vertex) to reduce the uncertainty, then the goal could be reached with open-loop actions.

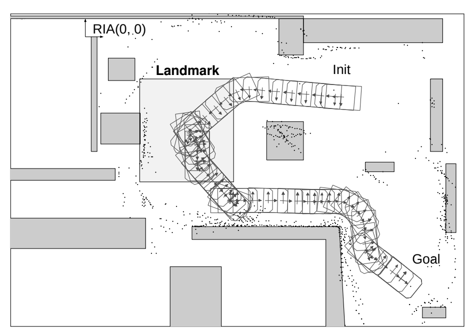
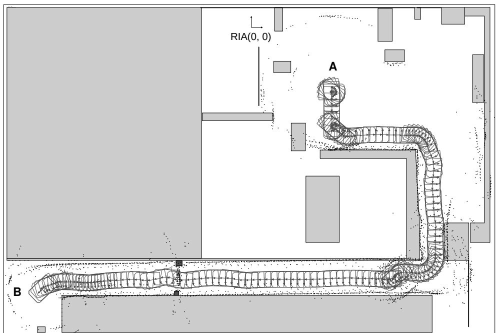


Figure 7: Experiment 2

The experiment of figure 7 corresponds to a case where the wall cannot be reliably reached with open-loop actions, because of their uncertainty evolution. The motion plan first reduces the position error by using the landmark zone before seeking the contact with the wall.




```
MOVE(dteta=-.57 , l=1.64)
MOVE_UNTIL_CONTACT(dcontact=.13 , Lmax=.48)
MOVE_ARC(dteta=.35 , r=1.05)
FOLLOW_WALL(side=RIGHT , d_wall=.34 ,
        wall0=(L1=2.03 , L2=.59, corner=(type=CVX , dtet=-1.51)),
        wall1=(L1=5.22 , L2=.38, corner=(type=CVX , dtet=-1.57)),
        wall2=(L1=.29 , L2=.0))
MOVE_ARC(dteta=.34 , r = 1.05)
MOVE_UNTIL_CONTACT(dcontact=.07 , Lmax=.27)
MOVE_ARC(dteta=-.35, r=1.05)
FOLLOW_WALL(side=LEFT, d_wall=.34,
        wall0=(L1=14.11 , L2=2.41,corner=(type=CVX , dtet=1.57)))
MOVE(dteta=.08, l=1.16)
MOVE(dteta=.7 , l=.68)
```

Figure 8: Experiment 3

Finally, a more significant task is shown in Figure 8. Starting with a rough estimate of its initial position (A) inside the laboratory, the robot has to cross a constrained doorway and then to move in a long corridor in order to reach the goal (B), and finally to go back. to the initial position (A). The robot executed this 60 meters roundtrip from the motion plan computed by the planning component, and shown in Figure 8. One can note that this navigation task would have been hardly feasible with open-loop motions because of the important traveled distance in a rather constrainted environement. This task, performed with our sensor-based planning and control algorithms, was successful almost at every execution.

References

[1] B. Bouilly, T. Siméon, and R. Alami. A numerical technique for planning motion strategies of a mobile robot in presence of uncertainty. In *IEEE International Conference on Robotics and Automation, Nagoya (Japan)*, 1995.

[2] J.L. Crowley. World modeling and position estimation for a mobile robot using ultrasonic ranging. In *IEEE International Conference on Robotics and Automation, Scottsdale (USA).*, 1989.

[3] A. Hait, T. Simeon, M. Taix. Robust motion planning for rough terrain navigation. *IEEE International Conference on Robots and Systems*, Korea, October 1999.

[4] O. Khatib. Real-time obstacle avoidance for manipulators and mobile robots. *The International Journal of Robotics Research*, 5(1):90–98, 1986.

[5] B.H. Krogh and C.E. Thorpe. Integrated path planning and dynamic steering control for autonomous vehicles. In *IEEE International Conference on Robotics and Automation, San Francisco (USA).*, 1986.

[6] J.C. Latombe. *Robot Motion Planning*. Kluwer Academic Publishers, 1991.

[7] A. Lazanas and J.C. Latombe. Motion planning with uncertainty: a landmark approach. *Artificial Intelligence*, 76:287–317, 1995.

[8] J.J. Leonard and H.F. Durrant-Whyte. Mobile robot localization by tracking geometric beacons. *IEEE Trans. on Robotics and Automation*, 7(3):376–382, 1991.

[9] S.M. La Valle and S.A. Hutchinson. Evaluating motion strategies under non deterministic or probabilistic uncertainties in sensing and control. In *IEEE International Conference on Robotics and Automation, Minneapolis (USA)*, 1996.

[10] M. Khatib and R. Chatila. An extended potentiel field approach for mobile robot sensor-based motions. *Intelligent Autonomous Systems (IAS'4), Karlsruhe (Germany)*, 1995.

[11] M. Khatib, B. Bouilly, T. Siméon, R. Chatila. Indoor Navigation with Uncertainty using Sensor-Based Motions. In *IEEE International Conference on Robotics and Automation, Albuquerque (USA)*, 1997.

[12] F. De la Rosa, C. Laugier, and J. Najera. Robust path planning in the plane. In *IEEE Trans. on Robotics and Automation, vol 12(2)*, 1996.

[13] R. Pissard-Gibollet P. Rives and K. Kapellos. Development of a reactive mobile robot using real time vision. In *International Symposium on Experimental Robotics, Kyoto (Japan)*, 1993.

[14] T. Siméon, R. Alami. Planning robust motion strategies for a mobile robot in a polygonal world. *Revue d'Intelligence Artificielle, Vol. 8, n° 4, p383-401*, December 1994.

[15] H. Takeda, C. Facchinetti, and J.C. Latombe. Planning the motions of a mobile robot in a sensory uncertainty field. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 16(10):1002-1017, 1994.