Proceedings of the 2000 IEEE
International Conference on Robotics & Automation
San Francisco, CA • April 2000

Combination of Model-based and Reactive Methods in Autonomous Navigation

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Abstract

The paper presents three contributions to autonomous navigation of mobile robots: (1) a purely reactive method based on the potential field theory enhanced with a novel procedure to avoid local minima; (2) a topological map building method based on the sensory gradient concept that combined with the reactive module constitutes a hybrid navigation system and (3) another navigation system that uses the so called robot's behaviors to automatically build a complete navigation model of the environment. All these schemes have been implemented on a Nomad-200 platform and fully tested in indoors environments.

1. Introduction. A Taxonomy for Navigation Methods

Most of the navigation methods for mobile robots are based on the use of models of the environment. Obviously the specific characteristics of the navigation world – i.e. indoors or outdoors, static or dynamic, structured or unstructured, etc.– determines the type and the creation process of the environment models. The exception to the standard model-based navigation systems are the so-called reactive systems which do not employ maps of the environment.

The well-known, almost universally accepted PPA paradigm for the design of autonomous robots considers them to be formed by three subsystems: (1) Planning, (2) Perception and (3) Action. The model-based navigation methods wholly integrate the three subsystems, whereas the reactive navigation systems only include the Perception and Action subsystems as they do not possess reasoning and planning abilities and are restricted to the interaction between Perception –usually the inputs of the system– and Action –normally the outputs of the system.

Despite of their lack of planning and reasoning faculties the reactive navigation schemes have interesting features like their ability to adapt to very dynamic, complex environments that are prohibitive for model-based methods. For this reason is very advisable to integrate in the same mobile robot both kind of schemes. Summarizing, for the taxonomic classification of the navigation systems a first feature to be considered is whether or not the navigation is model-based; i.e. *formal and reactive navigation* respectively. *Hybrid* navigation integrates both methods in the sense that each navigation scheme acts autonomously albeit in coordination with the other one.

Figure 1 shows the taxonomy of navigation schemes for mobile robots. Each branch of the tree structure is generated by different altenatives in the corresponding feature.

There is an additional distinction in the formal or model-based navigation methods depending on whether the environment models are a priori fixed or variable through a learning process after exploratory missions undertaken by the robot in order to build a map of the environment. Therefore a second taxonomic feature refers to the dichotomy between *rigid and adaptive* modelling of the environment.

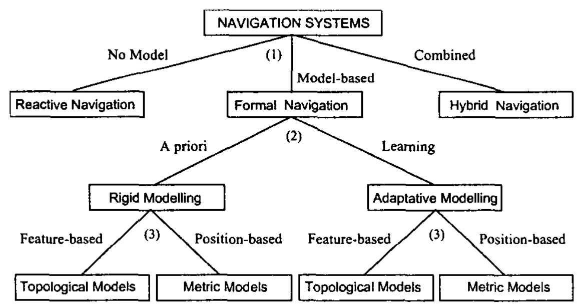

Figure 1. Tree structure for the taxonomic classification of mobile robots navigation methods. Numbers from 1 to 3 indicate the feature. Branches are formed by different possibilities in features. Nodes are specific type of navigation schemes.

Each type of formal navigation schemes –i.e. rigid and adaptive– can be further classified into *topological or metric*. In metric models the precise, numerical position and orientation of the robot is needed for navigation purposes whereas in topological models the navigation information is qualitative rather than quantitative. Therefore the distintion between metric and topological models is the third and last taxonomic feature.

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Keeeping in mind the above classification of autonomous navigation methods for mobile robots this paper presents the following contributions.

(1) A pure reactive navigation algorithm based on the well-known potential field theory [4] with a novel mechanism to avoid the frequent deadlocks produced by local minima.

(2) A first method for the automatic creation of topological maps using a novel concept: the sensory gradient.

(3) A second method for the automatic generation of topological maps that do not employ sensory information from the environment.

According to the taxonomic classification previously proposed , contribution (1) belongs to the reactive navigation category and contributions (2) and (3) belong to the formal, adaptive, topological navigation category.

In the Nomad-200 mobile platform used to test our navigation methods we have implemented two independent navigation systems. One of them is a hybrid scheme that combines contributions (1) and (2). The other system is based exclusively on contribution (3). In the sequel both navigation systems are described in separate paragraphs.

2. A Hybrid Navigation System

Hybrid systems enlarge the standard model-based methods with reactive abilities that have proved to be excellent for very low-level navigation tasks in complex, unknown and variable environments. On the other side, the disadvantages of pure reactive navigation originated from its lack of planning and reasoning capacities are overcome in hybrid systems by incorporating model-based schemes. Therefore hybrid systems combine the low-level navigation ability of reactive systems with the high-level navigation ability of topological model-based schemes.

Our hybrid system is composed of two subsystems: (1) a reactive navigation module and (2) a topological model builder that detects what we call *relevant sensory places* (RSPs) as landmarks of the environment map. These RSPs form a quite simple network that allows a straightforward computation of minimum cost routes –i.e. the high-level navigation tasks- that will be used by the reactive module for the low-level navigation tasks.

The reactive navigation module is based on the artificial potential field theory enhanced with a novel mechanism to avoid the frequent appearence of local minima that tend to block the robot actions. The model-based module employs a novel concept in reactive navigation –i.e. the sensory gradient- to detect the RSPs or landmarks. These navigation landmarks are linked by means of privileged navigation directions obtained from the sensory information processing on board the robot. Finally a planning module is in charge of the routes computation and the coordination with the reactive scheme.

2.1. Artificial potential fields and fictitious charges

The potential field theory [4] considers the robot as a particle within a potential field in which the local variations of the potential function represent the structure of the environment. The obstacles are modelled as repulsive forces charges and the final goal as an attractive charge. The robot movements are iteratively computed, obtaining at each step the force generated by the field and using its direction to generate the robot's trajectory. The purpose is obviously to guide the robot towards the goal without colliding with the obstacles. One of the serious drawbacks of the potential field theory is its high sensitivity to local minima that are unfortunately quite frequent. In order to escape from local minima we have introduced a novel approach which is based on the use of what we call fictitious repulsive forces [6] that compel the robot to move away from any local minimum once it has been detected.

A local minimum can be detected taking into account the result of all the forces acting upon the robot. When the total force is very small the induced movement will be near zero and therefore the robot will have almost certainly fallen into a local minimum. The critical decision is to detect a possible local minimum when the total force acting on the robot is lower than certain threshold. In such a situation the proposed solution is to place a unity repulsive force which urges the robot to escape from the local minimum in the coordinates given by the expression:

$$\vec{p}_c = \psi(\vec{p}_r - \vec{S} + \vec{l}) \qquad (1)$$

where $\vec{p}_r$ is the current robot position; $\vec{S}$ is the repulsive force associated with the environment physical structure and $\vec{l}$ is a unity vector perpendicular to the vectorial force $\vec{G}$ pointing at the final goal. Ψ is a real number that determines the distance at the point where the fictitious charge is placed: in our case after empirical testing, twice the Nomad-200 radius; i.e. about 18 inches.

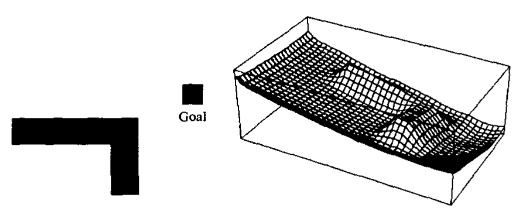


Figure 2. Example of local minimum in the potential field.

It must be remarked that there exist in the plane two vectors perpendicular to g and with opposite directions: left and right, that generate two different robot's movements. To select one of the two possible vectors we use the most natural trajectory; i.e. the one that differs in angle the least from the current robot`s direction.

If there are applied several fictitious charges the total force due to them has the following expression:

$$\vec{C} = \sum_i -\frac{k_c}{\left|\vec{C}_i\right|^{m_c}}\vec{c}_i \qquad (2)$$

where $\left|\vec{C}_i\right|$ is the distance between the robot and the fictitious charge i and $\vec{c}_i$ is a unity vector giving the direction of charge i. Two parameters, k and m determine the way the charge decays with distance. Ideally these parameters should be proportional to the local minimum's magnitude, albeit this magnitude is unknown at advance. After experimental adjustments we are using values as $k = 8$ and $m = 1$.

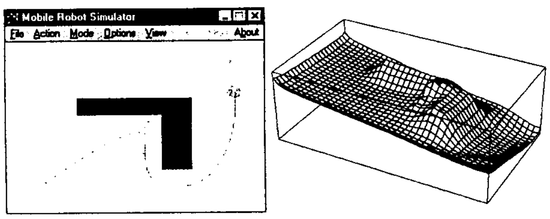


Figure 3. Five fictitious charges have been generated to escape from the local minimum. Notice the modified potential field profile as compared with figure 2 due to the introduction of the fictitious charges.

The introduction of the fictitious charges provokes an artificial elevation of the potential field surface allowing the robot to avoid the local minima without any external change in its navigation strategy as it is the case in standard methods for local minima avoidance. In figure 3 can be observed the effect of the fictitious charges created around the concave region of the object, responsible of the local minimum.

Latombe mentions a hypothetical potential function – the navigation function- that if obtained would allow the robot´s navigation towards the final goal by just applying a gradient-based descent procedure, [5]. Although this function do not exist in general or it is very hard to obtain our artificial fictitious charges method can be seen as a good approximation to such navigation function.

2.2. Landmarks detection using the sensory gradient and creation of topological maps

A purely reactive navigation scheme like the one just discussed is unable to exploit the knwoledge about the environment -be it a priori given or learned from exploratory missions of the mobile robot- and therefore it must be complemented with a model-based module. In previous work [7] we have proposed a topological model-based navigation method that employs what we call sensory gradient to detect landmarks of the environment. We define the sensory gradient as the vector derivative of a trajectory in the sensory space. This gradient can be estimated as the difference between the vectors representing the sensory readings in two successive instants divided by the elapsed time:

$$\nabla\vec{s} = \frac{\vec{s}(t+\Delta t) - \vec{s}(t)}{\Delta t} \qquad (3)$$

By applying the sensory gradient concept we can detect and identify landmarks and build upon them a graph-based model of the navigation world. Furthermore navigation plans or missions can be obtained by means of, among other techniques, the plan-as-communications method [1]. Figure 4(a) displays a network of landmarks or RSPs obtained using the sensory gradient idea. In figure 4(b) are shown the corresponding navigation privileged directions computed by means of the plan-as-communication concept. For details we refer to [7].

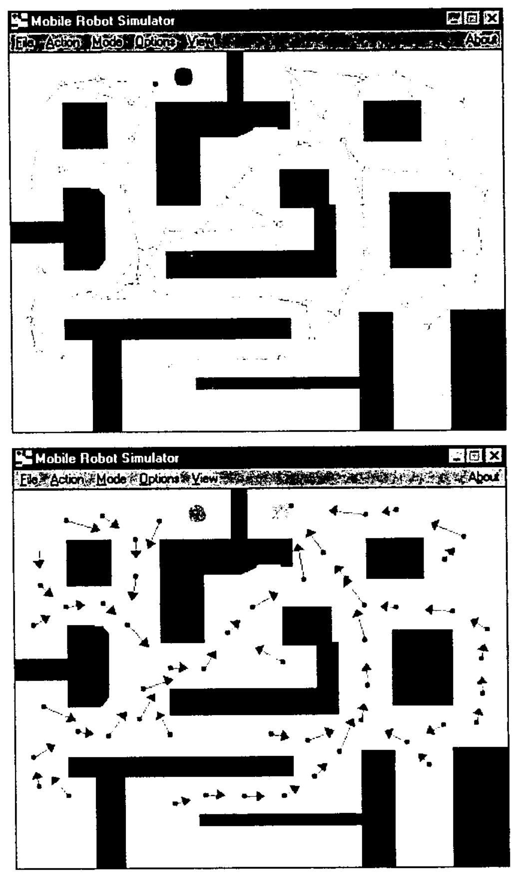


Figure 4. Part (a) represents the topological map obtained with the sensory gradient. Part (b) displays the navigation recommendations for each landmark.

3. A Behavior-based Navigation System

We have also implemented another navigation system based on a cyclical-execution architecture [2] which is able to simultaneously build topological models of the environment –i.e. the high-level navigation tasks– and execute low-level navigation tasks. In this system the processes associated with what we call the *navigation behaviors* of the robot are executed in a cyclical way so that one or more behaviors are activated depending on the environment state. A sequential activation of individual behaviors produces what we call *navigation tasks.*

We define three different groups of navigation behaviors. The first group or *basic behaviors group* allows the robot to perform basic navigation operations like "go forward" and "obstacle avoidance". To this end three behavior patterns are used: (a) **advance**, that makes the robot to move in straight line and which is the basic behavior needed by the robot in order to come back after performing a concrete navigation manoever; (b) **lateral avoidance,** that corrects the robot trajectory when a side collision is foreseen and (c) **frontal avoidance**, that produces a turn whenever an obstacle is detected in front of the robot. This three simple pattern behaviors make possible the implementation of collision-free trajectories.

The second group of behaviors or *navigation strategies group* is formed by the behaviors that makes the robot to properly activate the basic behaviors depending on the environment specific structure. In particular, we define four different navigation strategies: (a) **wall and obstacle following**, that generates a trajectory along the wall or the obstacle contour; (b) **detour**, that uses the obstacle as a reference for trajectory modifications and permits high-level commands like "take the first cross at right"; (c) **turn**, that causes a change in the movement direction of up to 180 degrees and (d) **free-movement or wandering** in which the robot moves along without colliding with any obstacle. In figure 5 two different trajectories obtained with (a) the obstacle following strategy and (b) the detour strategy are displayed.

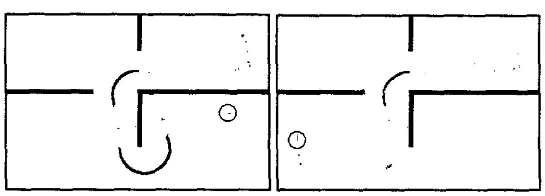


Figure 5. Trajectories obtained with (a) obstacle following strategy and (b) detour strategy.

The third and last group of behaviors or *operating behaviors group* includes those behaviors needed for high-level navigation tasks. Among them we point out those in charge of selecting the appropiate robot task- for instance, activation of an exploration mission to build environment maps or activation of an execution mission to reach a specific goal- and those in charge of monitoring the robot's internal states.

All the behaviors follow a cyclical-execution architecture based on the PPA paradigm –i.e. Planning, Perception and Action cycles– and organized in two levels: supervision and performance. In the supervision level all possible events for the activation of any behavior are under continuous control and surveillance. The performance level is responsible of the decision making about the activation and coordination of the behaviors. During the Perception cycle the system inputs can stem from either the physical sensors or from internal events generated by the navigation system itself. Similarly the Action cycle can induce either actuations over physical elements of the robot –for instance, a modification in the advance movement– or over the internal states of the robot navigation system itself –for instance, an updating of the environment model–.

3.1. Reference Places Detection and Model Building.

For the robot's internal representation of the environment we have chosen a topological model based on Fuzzy Petri Nets (FPN) that allows to simulteneously identify the places of the FPN with the reference places or landmarks and the transitions of the FPN with the navigation strategies linking the landmarks.

The model building is automatically performed by the robot during the exploratory missions in which the robot detects the different landmarks and tests different navigation strategies for each landmark. Whenever one of the trials leads to a new landmark the model of the environment is updated. In figure 6 an instant of the robot navigation in an office room and the corresponding topological model obtained by the robot are shown. The circles in the map are the detected landmarks and the arrows represent the privileged direction for the navigation strategy to reach the nearest landmark.

Most of the autonomous navigation methods based on topological models use directly the sensory information as the main source for the detection and recognition of the reference places like the system described in the previous paragraph that uses the sensory gradient for that purpose. Our second navigation system instead of using sensory information exploits the information supplied by the navigation system itself. The changes in the behaviors -some of them previously defined- of the navigation system generated by the structure and physical characteristics of the environment allow the detection of the reference places or landmarks. Figure 7 shows three examples of landmark creation. In all of them the robot navigation system abandons its current navigation behavior in order to avoid collisions with the obstacles –i.e. the wall in front of it–. These situations are recognized as reference places because the robot must abruptly change its trajectory and therefore they can be used for the environment modelling and for future planning of navigation missions.

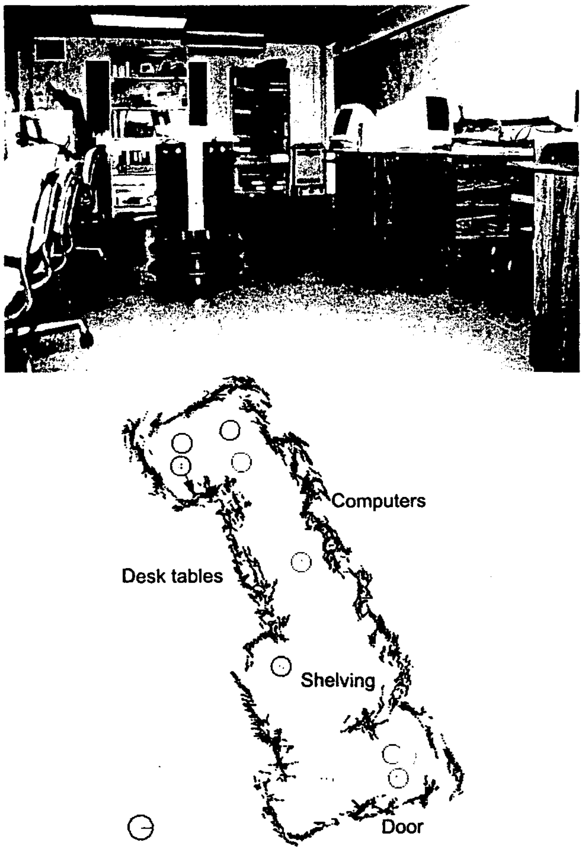
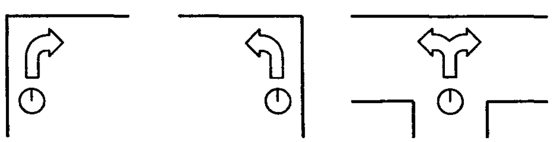


Figure 6. An example of environment model building.



(a) (b) (c)

Figure 7. Instances of typical landmarks detection.

3.2. Route Planning and Execution.

Once the environment model has been built the mobile robot can perform any type of navigation mission. Basically two phases in route planning and execution can be distinguished: (1) model search and (2) model tracking. During the model search phase the robot detects and identifies some of the already created landmarks so that its position is updated. During the model tracking phase the robot must test the strategies suggested by the navigation model until it reaches a new landmark.

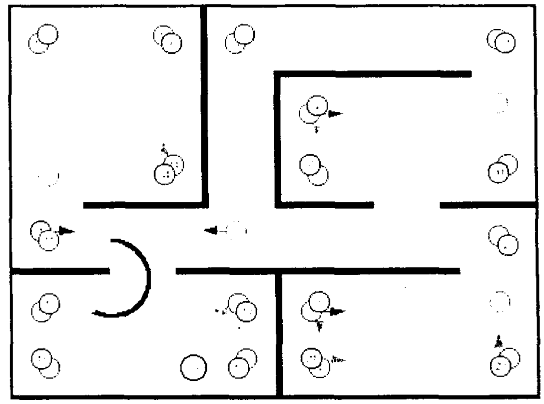


Figure 8a. Example of navigation mission based on the environment models previously built by the robot.

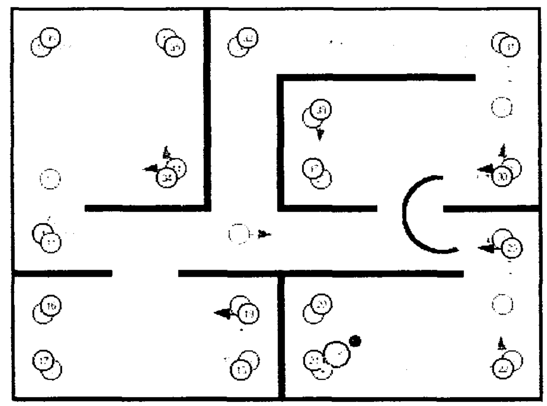


Figure 8b. Another example of navigation mission based on the environment models previously built by the robot.

For route planning a minimum cost algorithm of the FPN's propagation values has been implemented [3]. Figure 8 shows two examples of route planning. For each case the arrows provide the turn to be applied and the corresponding navigation strategy to follow.

4. Conclusions

We have proposed a taxonomic classification of the numerous existing autonomous navigation methods in which we consider three taxonomic features: model-based versus reactive schemes, fix versus variable modelling and topological versus metric maps. Afterwards the paper expounds and discusses three contributions to the autonomous navigation topic: (1) a purely reactive method based on the potential field theory enhanced with a novel procedure to avoid local minima, (2) an autonomous topological map building method based on the sensory gradient concept that combined with the reactive method constitutes a hybrid navigation system and (3) another navigation system that uses different robot's behaviors to automatically build topological maps of the environment and that based on Fuzzy Petri Nets is able to plan and execute navigation missions. All these methods have been implemented on a Nomad-200 platform and thoroughly tested in office-like environments.

Acknowledgments

The experimental work reported in this article has been partly funded by the Spanish Comisión Interministerial de Ciencia y Tecnología (CICYT) under contract TER96-1957-CO3.

References

[1] R. E. Agree, D. Chapman. What are Plans for? *Designing of Autonomous Agents*. P. Maes (ed.). Cambridge, MA, MIT Press, 1990, pp. 17-34.

[2] J. de Lope. *Modelado de entornos con técnicas basadas en Redes de Petri Borrosas para la exploración y planificación de robots autónomos*. PhD Thesis Dissertation. Computer Science Faculty, Technical University of Madrid, 1998.

[3] J. de Lope, D. Maravall and J.G. Zato. Topological modeling with Fuzzy Petri Nets for autonomous mobile robots. In A.P. del Pobil, J. Mira and M. Ali, editors, *Proc. of the 11th Int'l. Conf. on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems, IEA-98-AIE, Lecture Notes in Artificial Intelligence 1416*, Springer-Verlag, Berlin, 1998, pp. 290-299.

[4] O. Khatib. Real-Time Obstacle Avoidance for Manipulators and Mobile Robots. *The International Journal of Robotics Research*, Vol. 5, No. 1, Spring 1986, pp. 90-98.

[5] J. C. Latombe. *Robot Motion Planning (3^{rd}. ed.)*. Kluwer Academic Publishers, Boston, 1993.

[6] F. Serradilla, D. Maravall. A Navigation System for Mobile Robots Using Visual Feedback and Artificial Potential Fields. *Proceedings of The Thirteenth European Meeting on Cybernetics and System Research*. Trappl, R (ed.), April 1996, pp. 1159-1164.

[7] F. Serradilla, D. Maravall. Cognitive Modelling for Navigation of Mobile Robots Using the Sensory Gradient Concept pp. 273-284. In Pichler, F.; Moreno-Díaz, R. (eds.) *Computer Aided Systems Theory – EUROCAST'97. Lecture Notes in Computer Science*. Springer-Verlag, Berlin, 1997, pp. 273-284.