

A hybrid architecture for autonomous navigation in dynamic environments

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ABSTRACT

This paper presents a hybrid architecture for autonomous robot navigation. It includes a deliberative layer that hierarchically extracts a global path from a geometrical-topological model of the environment. This path is decomposed into a set of partial goals. Then, a new case-based reasoning based reactive layer capable of learning new local navigation strategies moves from each partial goal to the next. The architecture has been successfully tested in real dynamic environments.

KEY WORDS

deliberative planning, reactive navigation, hybrid layered architecture, case-based reasoning

1 Introduction

Navigation can be defined as the act of finding and tracking a safe path to a defined goal. Autonomous robotic navigation has been widely studied in the last decades. Proposed techniques range from high-level planning schemes to reactive control strategies. High level planning methods require extensive world knowledge so the robot can act in a predictable efficient way. These methods typically rely in a classic *sense – model – plan – act* cycle known as horizontal decomposition [8]. Deliberative schemes are often criticized for their inability to react rapidly. Also, since they strongly depend on a world model, they are not suitable to operate in partially or totally unknown environments nor in significantly dynamic ones [1]. Reactive control methods rely on directly coupling sensors and actuators [3]. Combinations of reactive behaviours return emergent actions. Unlike classic deliberative systems, reactive schemes can easily deal with several sensors and goals. Besides, they are flexible and quite robust against sensor errors and noise. Unfortunately, emerging behaviours may be very unpredictable and, in some cases, non-efficient. Reactive systems are also prone to fall into local traps. Hybrid systems combine deliberative and reactive schemes to achieve a better performance. Usually, low level control is performed in a reactive way whereas high level processing follows a deliberative pattern. Hybrid systems are supported

by biological evidence [1] and they can achieve efficient navigation in dynamic and totally or partially unknown environments.

This paper presents a hybrid scheme for autonomous navigation in dynamic environments. Our scheme is based on decomposing tasks in layers as proposed by Brooks [3]. High level layers reason about the environment and propose a global path to the goal. Low level layers are in charge of safely reaching that goal according to guidelines proposed by the high level layers. Section 2 presents a brief global description of the system, outlining the differences between this proposal and previous ones by the authors. Section 3 presents our high level path planning technique plus a world modelling technique. Section 4 presents a new CBR based reactive layer. The main novelty of the proposed architecture is this trainable reactive layer and its integration into the hybrid architecture. Section 5 presents experiments and results for the complete hybrid structure. Finally section 6 presents conclusions and future work.

2 Proposed hybrid scheme

As aforementioned, hybrid systems combine deliberative and reactive schemes in order achieve a better performance. Usually, low level control is performed in a reactive way whereas high level processing follows a deliberative pattern. The main concern when building a hybrid scheme is to find the appropriate boundary for the subdivision of functionality [1]. We propose an advising scheme where navigation is performed in a bottom-up way: the successively combined responses of the low level layer provide a global goal-reaching navigation behaviour. This hybrid structure is particularly interesting for dynamic and partially explored environments because the system can immediately react in an efficient way to unexpected obstacles and high level planning avoid local minima by providing intermediate goals for the low level layer.

Our hybrid navigation architecture basically consists of four layers (Fig. 1). First, a *geometrical modelling layer* uses the on-board sensors to construct and update an evidence grid as proposed in [12]. Then, the

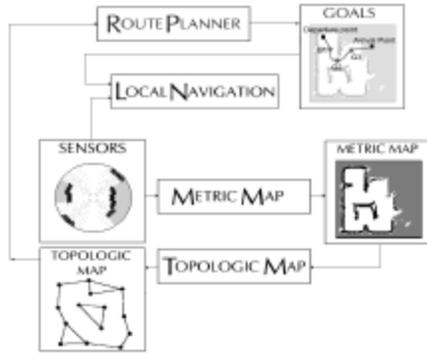


Figure 1. Proposed hybrid scheme.

grid is processed by the *topological modelling layer* to obtain a topological map proposed by the authors in [17]. Both the geometrical and topological maps are updated as often as possible so that reasoning is always performed over the most recent model available. Our deliberative layer is known as *route planner*. It is in charge of calculating an efficient global path free of obstacles between a departure and an arrival point as proposed in [17]. This layer is triggered each time a new goal is proposed but also when the topological map suffers significant changes in areas where the robot is operating. It must be noted that this layer is quite fast. Hence, it is not necessary to stop the robot while calculating a new deliberative route. Instead, navigation is reactively handed until a new goal is provided. Paths calculated at topological level can be immediately propagated into path regions at metric level. These regions were the output of the deliberative layer in our previous scheme [17]. However, in the current one we thin the region into a path and decompose that path into segments which can be tracked with minimum curvature changes. The joints of these segments become partial goals to the robot and are the output of the *route planner*. Instead of tracking the path in a deliberative way as we did in [16], our *local navigation layer* relies on a reactive scheme to move safely between consecutive partial goals. A first version of this architecture was proposed in [17]. However, in [17] the reactive layer was based on potential fields. In this work, we have developed a new reactive layer based on CBR (Case-Based Reasoning). Its advantages with respect to potential fields are described in section 4.

The proposed hybrid architecture works in an efficient way because: i) the deliberative layer proposes efficient paths to arrive to a goal; ii) these paths are tracked in a fast reactive way to handle sensor errors and unexpected situations; iii) the environment is represented at two hierarchical levels so that it can be

both updated and processed in a fast way; and iv) the local navigation layer may work even when the output from higher level layers is outdated. Thus, the robot does not need to stop when a given path needs to be recalculated because of unexpected obstacles in the way. This architecture has been successfully tested in real indoor environments using a Pioneer robot.

3 Deliberative path planning

Deliberative navigation algorithms rely on world models either provided a priori or built by means of the on-board sensors. These models can be processed by any classic planning algorithm to calculate a safe trajectory. Representations of the environment are usually built according either to the metric or the topological paradigm. Metric representations, most typically evidence grids [12], explicitly reproduce the metrical structure of the environment. Topological representations aim at representing the environment as a set of meaningful regions. Both approaches present complementary strengths and weaknesses [13]. Metric approaches heavily rely on dead-reckoning. Also, they may involve a huge data volume and, hence, be computationally expensive to process. Topological maps are usually more compact because their resolution is determined by the complexity of the environment. They support fast planning and provide more natural interfaces for human instructions. However, in topological maps it is difficult to distinguish different places characterised by the same sensory pattern and non-explored areas are not included in the representation. Some authors propose a combination of both topological and geometrical representations by annotating topological maps with metrical information [10] or extracting topological maps from metric ones [13]. The authors proposed in [17] a method to extract a grounded topological map from an evidence grid:

1. Metric map thresholding. Cells whose occupancy value is below threshold U_1 are considered free-space ($P(x, y) = c_F$). Cells whose occupancy value are above U_1 and below threshold U_2 are considered non-explored ($P(x, y) = c_N$). All other cells are considered occupied ($P(x, y) = c_O$) (Fig. 2.a).
2. Hierarchical structure generation. The thresholded metric map becomes the base of a pyramidal structure. Each level l of this pyramid is a reduced map with $1/4$ of the cells of the level immediately below. Each pyramid cell (x, y, l) has associated five parameters:
 - Homogeneity, $H(x, y, l)$. $H(x, y, l)$ is set to 1 if the four cells immediately underneath have the same occupancy probability and their

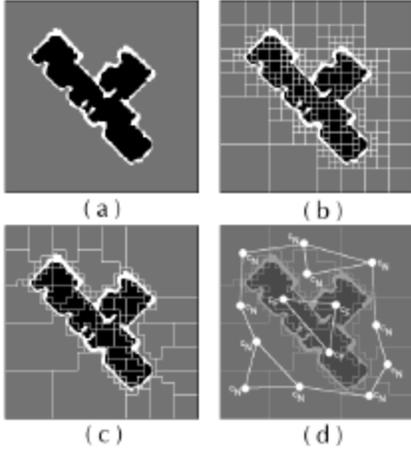


Figure 2. Topological map extraction: a) thresholded grid; b) hierarchical split; c) interlevel merging; d) intralevel merging and resulting topological map.

homogeneity values are equal to 1. Otherwise, it is set to 0.

- Occupancy probability, $P(x, y, l)$. If the cell is homogeneous, $P(x, y, l)$ is equal to the occupancy probability value of any of the four cells immediately underneath. If the cell is not homogeneous, the value of $P(x, y, l)$ is set to a fixed value (c_{NH}).
- Area, $A(x, y, l)$. It is equal to the addition of the areas of the four cells immediately underneath.
- Parent link, $(X, Y)_{(x, y, l)}$. If $H(x, y, l)$ is equal to 1, the values of parent link of the four cells immediately underneath are set to (x, y) . Otherwise, these four parent links are set to a null value and they become orphan nodes.
- Centroid, $C(x, y, l)$. It is the centre of mass of the base region associated to (x, y, l) .

When the generation step has finished, all orphan cells presenting an homogeneity value equal to 1 are associated to a partition where complexity strongly depends on the position of the obstacles (Fig. 2.b). Further steps remove this problem.

3. Homogeneous cells fusion (Fig. 2.c). Cells whose parent link values are null, (x, y, l) , are linked to the parents of neighbours cells, $(x_p, y_p, l + 1)$, if the following conditions are true:

- $H(x, y, l) = 1 \ \& \ H(x_p, y_p, l + 1) = 1$
- $P(x, y, l) = P(x_p, y_p, l + 1)$
- $\|C(x, y, l) - C(x_p, y_p, l + 1)\|_2 < DistMax$ (threshold to fix the maximum dispersion of resulting regions).

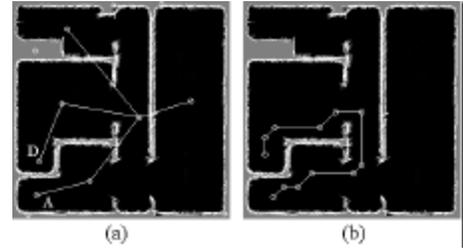


Figure 3. Deliberative path calculation: a) topological-metrical map, departure and arrival points; b) resulting trajectory and partial goals.

4. Homogeneous cells classification (Fig. 2.d). Two neighbour cells, (x_1, y_1, l) and (x_2, y_2, l) , are fused if the following conditions are true:

- $(X, Y)_{(x_1, y_1, l)} = NULL$
- $(X, Y)_{(x_2, y_2, l)} = NULL$
- $H(x_1, y_1, l) = 1 \ \& \ H(x_2, y_2, l) = 1$
- $P(x_1, y_1, l) = P(x_2, y_2, l)$
- $\|C(x_1, y_1, l) - C(x_2, y_2, l)\|_2 < DistMax$

Fig. 2.d shows the grid of a real environment and its associated topological map after this final step is accomplished. Each orphan cell is related to an homogeneous region which becomes a topological node. Two nodes are linked if they correspond to adjacent regions and they are not related to occupied areas. In the corridor in Fig. 2.a there are only three nodes related to free areas: the north west and south east parts of the corridor and the square lab in the middle. These three nodes are linked together because it is possible from one to any of the others. Walls are not included in the topological map because they correspond to occupied areas. The rest of the nodes are related to non-explored areas, but they can not be reached from within the corridor because all doors are closed. This means that the robot can not currently reach unexplored areas. The advantages and drawbacks of this topological-metrical map are fully described in [17].

In the proposed topological map, complex areas are related to a large number of nodes while simple ones are related to a few. Path planning algorithms, in our case the A* algorithm [17], work at topological level. The resulting path of nodes is linked to a path region including the departure and arrival points at metrical level. In our former hybrid architecture [17], the output of the deliberative layer was this region. However, in the present work, this region is transformed into a path of cells as proposed in [16] by means of a fast wave propagation algorithm. The main novelty of this deliberative layer is that we do not work with the whole path. Instead, we extract the points of maximum curvature from the path. Those points become partial goals because the robot can easily travel

between them with minimum curvature changes. Fig. 3.a shows an topological-metrical map and random departure and arrival points, while Fig. 3.b shows the resulting trajectory plus the partial goals for this particular example. It can be observed that partial goals are not nodes of the topological map. Furthermore, they are defined at metrical level.

It must be noted that the robot does not try to track the deliberative path as initially proposed in [16] because slippage, unexpected obstacles and other external factors make it very difficult to pursue a fixed trajectory. Instead, it simply tries to reach the final goal by flexibly moving from each partial goal to the next. Sometimes, the aforementioned factors may make a global route unfeasible despite the reactive navigation layer. However, since the map is modified on-line, if new detected obstacles make it impossible to reach a partial goal, the deliberative layer is retriggered to calculate a new trajectory from the current position to the goal [17].

4 A reactive navigation layer

The potential fields method is probably one of the most popular ones for reactive navigation both in dynamic and static environments [18]. It consists of creating an artificial repulsion field around the obstacles in the environment plus an attraction field around the goal so that the robot moves towards that goal and away from the obstacles. Despite their simplicity and efficiency, potential fields also present some drawbacks. First, they make it difficult to move between close obstacles. They also tend to present oscillations close to occupied areas and they are not efficient for navigating close to an obstacle. The most important drawback, though, is that they may converge to local minima. Alternatively, some non-purely reactive approaches based in a world model have been proposed (i.e. [5] [15]). The main drawback of these approaches is that they depend on many parameters which are difficult to optimize except for ad-hoc problems.

We used a potential field approach in a previous hybrid navigation scheme [17]. The deliberative layer avoided potential fields from falling into local minima. However, our previous scheme did not support navigation between close obstacles nor learning. The main novelty of the present work is a new CBR (Case Based Reasoning) reactive layer. CBR has been defined as reasoning by remembering [9]. A *case* can be regarded as a vector in an N-dimensional space. When a potentially interesting situation is detected, a CBR cycle consists of four steps: i) retrieve the most similar stored *case*; ii) adapt its solution to the current *case*; iii) evaluate the results; iv) learn from the new experience. CBR has been used in navigation before either for global path planning in static environments [4] [2] or for behaviour selection (i.e. [14]). In

these cases, CBR is meant to recall the structure of a particular environment because no deliberative layer is supposed to exist. Naturally, in dynamic environments these approaches may turn unefficient because cases may become quickly obsolete. In our approach, the CBR-based layer cooperates with a deliberative layer and, hence, it stores no information about the environment. Instead, it is simply meant to efficiently avoid unexpected and moving obstacles in the way according to guidelines which are valid for local geometric obstacle configurations. Our deliberative layer also prevents in this case the reactive layer from falling into local minima by providing intermediate goals globally calculated and by recalculating complete routes when there have been severe changes in the structure of the environment after the last global planning.

4.1 Case definition

A *case* is defined by the attributes conforming the input vector, how solutions can be adapted and how results are evaluated. The attributes required to define a pure reactive layer are basically the sensor readings and the goal. If no deliberative layer is available, either a time sequence of sensor readings [14] or a explicit model of the environment [11] is required. In our case, we simply operate with the readings of 8 on-board Polaroid sonar sensors at a given time instant. To avoid having too many cases derived from small perception differences, we discretize sonar readings into 5 intervals: i) critical (0-20 cm); ii) near (20-50 cm); iii) medium (50-100 cm); iv) far (100-150 cm); and v) no influence (150-800 cm). As aforementioned, the closest partial goal is also added to the case attributes. Since we do not use a model of the environment in the reactive layer, we can not represent the goal by means of coordinates. Instead, we simply include the direction of a vector joining our current position to that goal. Using this information, the system must return a new heading direction for the robot to safely reach the goal in that particular situation.

Since the robot must adapt itself to dynamic environments, the solution to a single case can not be judged good or bad in terms of arriving to a partial goal which, in some cases, may be unreachable. Instead, we evaluate solutions by using three simple local criteria. In order to provide some temporal inertia against sonar noise and to prevent slippage as much as possible, we try to minimize curvature changes in the robot trajectory. The second evaluation factor is the angle between the robot-goal vector and the advance direction, so that the robot avoids getting too far from its partial goal. Finally, in order not to get too close to obstacles, the smaller sonar reading is also included as an evaluation factor. Fig. 4 shows how a case is defined for a robot equipped with 5 sensors and heading to the direction marked by the black arrow.

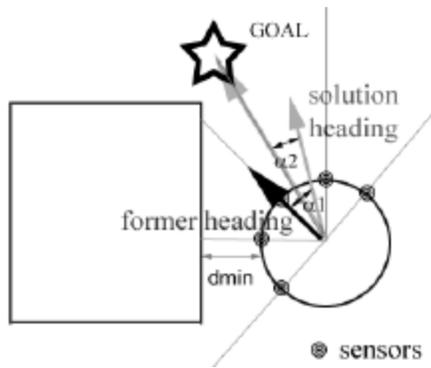


Figure 4. Case definition

The attributes of the case are the readings of the 5 sensors plus the goal direction, which is marked with a grey arrow. The resulting vector is the large one in gray pointing to the north of the image. Finally, the evaluated criteria are the shortest distance to obstacle d_{min} , the curvature variation $\alpha 1$ and the angle formed by the heading direction and the goal direction $\alpha 2$.

4.2 Training stage

Before the robot starts to operate on its own, we performed a supervised training stage off-line. This stage basically consisted of manually guiding the robot towards a goal blocked by a single obstacle. The robot was guided by three different persons through different routes, leaving the obstacle on the left or on the right of the robot. Cases were captured through this training stage each time the sensor readings experienced a significant change, where cases are compared by using the Tanimoto distance. In this training stage, the robot captured 160 cases after 6 routes. The main differences between these routes were basically how soft curvature changes were and how close to obstacles the robot got depending on the relative position of the goal. Unlike analytical approaches that tend to behave in an homogeneous way, a human driver can get close to obstacles if necessary depending on many different criteria. Thus, we wanted the robot to learn when it is better to navigate close to obstacles and when to navigate far from them depending on the training and the optimization criteria proposed in the previous section. Ultimately, we wanted to make the robot choose the most suitable chain of actions to reach a goal by combining different drivers and routes. It must be noted that the robot does not learn complete routes. It simply learns adequate actions for a given sensor configuration. No solution on its own is enough to reach the goal. Also, no global trajectory information is stored. The robot only learns what the driver does in a given situation and how adequate that action was regarding the robot previous trajectory, the relative position of

the goal and the layout of the obstacles in that particular situation.

4.3 Emergent behaviours

Whenever a list of partial goals is available, the robot tries to reach the closest one ahead in a reactive way. Basically, it tries to reach that partial goal with as few curvature changes as possible. However, when obstacles are perceived by its sensors, the reactive layer is triggered and, if necessary, a new direction is provided for the robot. The new heading is the best possible one according to the sensor readings, the position of the goal and the current direction. As soon as the robot moves, the sensor readings change. If a new case appears, the reactive layer is retriggered and the robot may change its direction again. Besides, the system is constantly checking if the current partial goal has been reached. As soon as that partial goal is left behind, the robot aims for the next one from its current position, which might not necessarily be the previous partial goal. In some cases, the deliberative layer may change future partial goals while the robot is navigating in a reactive way if necessary. The final emergent behaviour should not be totally equal to any trajectory performed in the learning stage, but rather to a combination of the best cases previously learnt according to the current input chain of events.

In many cases, the closest case stored in the database might not be similar to the current one, specially when training has not been exhaustive. In these cases, the proposed solution might not fit the current requirements of the robot. To avoid unefficient and potentially hazardous decisions, if an input case is too different from the closest stored one, we mutate the proposed solution and store it as a new case. In this work, solutions are mutated by creating repulsion vectors for all obstacles at critical distance from the robot and subtracting them from the proposed solution. It must be noted that solutions are only mutated if the current case has no suitable match in the CBR yet.

Fig. 5 presents a real example of reactive navigation where no deliberative layer is active: the only goal is in front of the departure point. However, the robot must navigate between two close obstacles to reach it. This is a traditionally hard problem for potential fields. If we use a too large safety distance, the robot will not navigate between the obstacles. If the safety distance is low, the robot may crash into the second obstacle while trying to move away from the first one, as can be observed in the Fig.5 (continuous line). However, the CBR has several cases stored where the training drivers drove quite close to obstacles. The robot learnt that it does not necessarily need to move away from a close obstacle if the goal is ahead and there is no immediate collision danger. Hence, it can be appreciated in Fig. 5 that the robot reaches the goal by following

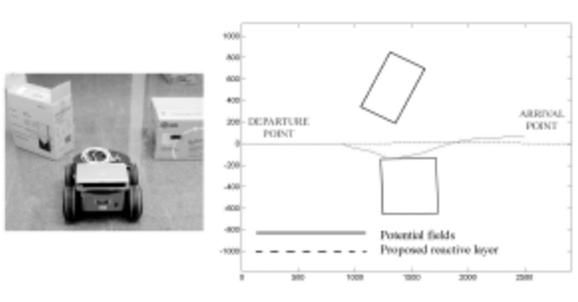


Figure 5. Emergent reactive behaviour

approximately a straight line (dashed line). It is interesting to note that the robot was trained for situations where a single obstacle was present in the environment. However, it can adapt itself to situations where there are more obstacles as well without deliberative advise.

5 Experimental results

To test the performance of the proposed hybrid architecture, several tests were performed in a real environment. The test environment was a 4x5 meters indoor laboratory presenting flat walls, cardboard boxes, metallic cupboards chairs and tables. We did experiment for non explored and partially explored environments, both with static and moving obstacles. This section presents some of these experiments. In all cases, each time we provide a goal, the deliberative layer calculates an efficient path to reach such a goal according to the available map. Maps are updated as often as possible. Thus, each time maps suffer significant changes, a new trajectory is calculated over the most recently updated map from the current position of the robot to the goal. As commented, deliberative trajectories are decomposed into a set of partial goals. The reactive layer is in charge of moving between each two consecutive partial goals. It must be noted that the reactive layer changes the robot trajectory not only when there is an obstacle in the way but also when there are obstacles close to the current path. If no obstacles are within the reactive layer perception range,



Figure 6. Environment layout for experiment 1

the robot tends not to change its deliberative trajectory and to follow a straight line towards the partial goal.

We present here two experiments for extreme cases. In the first one, the environment is partially explored before a goal is set and we purposefully prevented the deliberative layer from being retriggered to force the reactive layer to deal with all unexpected events. In the second case, we set a goal in a completely unknown environment where the metrical-topological map is continuously modified while the robot navigates towards the goal. Fig. 7.a presents the fully explored metrical map for our first experiment. It presents three nodes corresponding to free space plus 11 corresponding to non-explored areas. Thus far, all nodes are reachable. Nevertheless, in this experiment our path goes through explored space. Fig. 7.b shows the path proposed by the deliberative layer including all partial goals. It can be observed that partial goals basically appear where the robot must change its direction and where the layout of the environment is more complicated. In a first test, we let the robot navigate to its goal without changing the environment. Fig. 8.a shows the whole trajectory for this test. It can be observed that the trajectory is quite soft. It presents a soft oscillation at the beginning which is caused by sonar errors. It can also be noted that there is a sharp curvature change when the robot turns right to reach the final goals. It appears because cases are mutated to contemplate the narrow corridor conformed by the cardboard box and the cupboard on the right in Fig. 6. When cases are mutated, curvature is not preserved for the sake of safety. Nevertheless, after several mutations, these sharp curvature changes tend to disappear from the CBR database. Our second experiment in this layout consisted of including an unexpected cardboard box on the right of the robot at the beginning of the path (Fig. 6). Even though cardboard boxes are difficult to include in models because of sonar reflections, this box can be slightly appreciated in the upper part of the metric map in Fig. 7.b on the right of the resulting trajectory. It can be noted that the robot turns left until the box is no longer in the way and then it basically repeats the previous path. The final sharp curvature change leads to a softer final trajectory to the goal because the robot acquired a new case in the previous test.

Fig. 10 presents a test where the robot operates in a completely unknown environment. The environment layout in this particular experiment is presented in Fig. 9. The initial topological map presents 13 nodes and it is possible to move between all of them because, as far as the robot knows, there are no obstacles around (Fig. 10.a). It must be noted that this map would yield a single node if we had not fixed a *DistMax* threshold in the topological map extraction algorithm. In this situation, the resulting deliberative

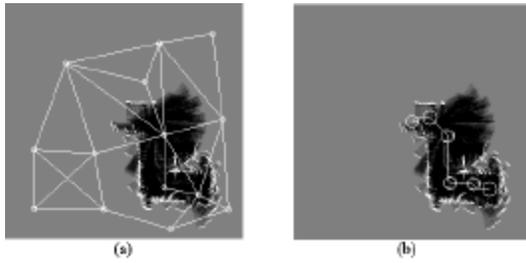


Figure 7. Deliberative path calculation: a) explored geometrical-topological map; b) resulting path and partial goals

path has a single partial goal (Fig. 10.a). As soon as the robot starts to move, the metrical map changes drastically and a new deliberative path is calculated to reach the goal in a more efficient way. Fig. 10.b shows the new topological and metrical maps. Behind the robot current position, the path resulting from the reactive layer can be observed. It can be noted that, despite the changes in the map, the position of the partial and final goals is practically the same than in Fig. 10.a. Also, it can be observed that a cardboard box is captured by the sensors on the right side of the robot. This box triggers the reactive layer and makes the robot turns slightly to the left to avoid it (Fig. 10.c). Then, the robot senses an obstacle in front of it. After mapping it both in the geometrical and topological representation, the position of the partial goal shifts down. After that newly detected obstacle is left on the left side of the robot, the deliberative layer decides that no intermediate goals are required anymore and that the goal can be reached in a straight way (Fig. 10.d). However, when the robot gets closer to the final goal, a wall is detected in its position, making it unreachable. Hence, the deliberative layer decides to stop. Fig. 10.e shows the final position of the robot, including the whole path tracked by the reactive layer. In that final path it can be clearly appreciated how the robot reacts to unexpected obstacles appearing too close to its path. It can also be appreciated both in Fig. 10.d and e that the robot moves between

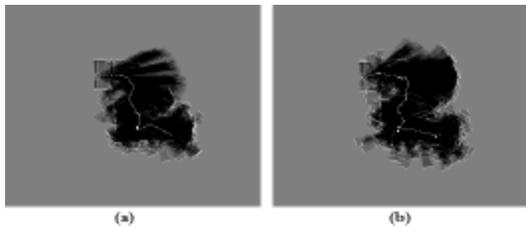


Figure 8. Resulting path for: a) no unexpected obstacles; b) unexpected obstacles

close obstacles with minimum oscillations (Fig. 9).

6 Conclusions

This paper has presented a hybrid scheme for autonomous navigation in dynamic environments. It relies on a geometrical-topological model of the environment. A deliberative layer calculates a global path at topological level and decomposes it into a set of partial goals at metrical level. Then, a reactive layer based on CBR is used to move the robot from goal to goal in a safe, efficient way. This layer is designed to learn local navigation strategies both supervisedly and unsupervisedly. The scheme has been successfully tested in real dynamic environments. Its main advantages are that it does not fall into local minima and it is capable of learning when it is necessary to navigate close to obstacles and when it is not. Further work will focus on improving the current localization strategy by taking advantage from the linked geometrical and topological models.

7 Acknowledgements

This work has been partially supported by the Spanish Ministerio de Ciencia y Tecnología (MCYT) and FEDER funds, project TIC2001-1758.

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Figure 9. Environment layout for experiment 2

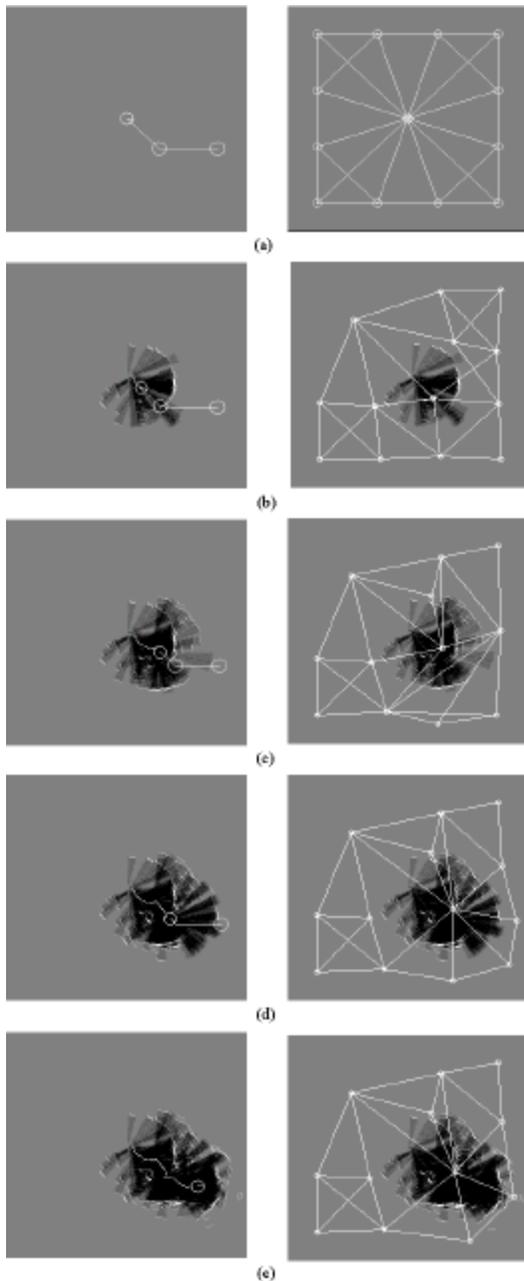


Figure 10. Experiment 2

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