



**HAL**  
open science

# Incremental Topological Modeling using Local Voronoi-like Graphs

Dominique van Zwynsvoorde, Thierry Simeon, Rachid Alami

► **To cite this version:**

Dominique van Zwynsvoorde, Thierry Simeon, Rachid Alami. Incremental Topological Modeling using Local Voronoi-like Graphs. IEEE/FSR International Conference on Intelligent Robots and Systems (IROS), Oct 2000, Takamatsu, Japan. hal-04292673

**HAL Id: hal-04292673**

**<https://laas.hal.science/hal-04292673>**

Submitted on 17 Nov 2023

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Incremental Topological Modeling using Local Voronoi-like Graphs

D. Van Zwynvoorde, T. Simeon, R. Alami

LAAS-CNRS

7, avenue du Colonel-Roche 31077 Toulouse Cedex - France  
{dzwyn,nic,rachid}@laas.fr

## Abstract

*In the field of mobile robotics, one important issue is to allow the robot to navigate in an a priori unknown and non specific large scale environment. Large dimensions raise strong limitations of geometric modeling, and topological or mixed metric-topological models are now studied to better fit the problem.*

*In this paper, we present a new method for incrementally building a topological model of an indoor environment from sensor range data. The approach consists in merging each local perception of the topology with the current state of the global graph. This local topology is captured through the construction of a Voronoi-like graph that takes into account not only visible features but also visibility constraints (hidden regions, limited sensing ranges, ...). We give the outline of the method and show first encouraging results on real data.*

## 1 Introduction

This paper addresses the issue of long term navigation in an *a priori* unknown, large scale environment. Large dimensions have dramatic consequences on localization since odometric pose estimate increasingly degrades as the robot moves around.

There exist some effective simultaneous map-building and localization methods (e.g [2, 3]) but they suffer from a rather costly learning scheme in terms of memory space and computation time. Indeed, they are based on localizing the robot in a global metric map of the environment, which becomes difficult in a large scale environment because of large position uncertainty. Some authors also defined sensor based strategies to deal with uncertainties [1, 4, 5, 6] but they assume some *a priori* knowledge and/or are limited to local navigation.

In such wide environments, a topological representation [8, 10, 11, 13, 14] may be more effective because it provides a compact model that allows fast route planning and reduces the amount of stored data, as well

as the computation time for learning. There are two common approaches to topological modeling.

Thrun [13] proposes a strategy that constructs a topological graph over a metric representation of the environment by partitioning the map into adjacent regions separated by narrow passages. It gains from both types of representation (metric and topological) but also suffers from the disadvantages of the metric map. Navigation techniques using such topological/metric descriptions have also been investigated (eg. [14] based onto Markov processes).

The other class of methods tries to construct a topological model directly from sensor data. In [11], Dubek proposes a hybrid topological-metric model where nodes of the topological graph are local metric descriptions of “*Islands of reliability*”. (see also [12] for a similar approach). Choset describes in [8] a sensor-based exploration procedure allowing a mobile robot to trace the Voronoi of the environment from sonar inputs. The system incrementally constructs a graph connecting *meet points* lying at the intersection of Voronoi’s edges. At each step, sonar data are used to maintain the robot onto the graph and to locally extend the edge currently traced with a single point.

Our topological model also derives from the Voronoi structure. However, the approach we propose to build this model exploits the richness of the information that can be collected by a laser rangefinder. Local Voronoi-like graphs are computed from the segmented range data and used to incrementally build the topological model. The potential interest of such approach is that matching local graphs with the partially constructed graph may allow to better maintain the reliability of the topological map.

The paper is organized as follows. Section 2 gives an overview of the approach. Section 3 presents how the local model is obtained from sensor data. Section 4 proposes a procedure for local merging of local and global models, along with a loop detection scheme to allow modeling cyclic environments. Section 5 gives some preliminary results on a real environment.

## 2 Overview of the Approach

The problem addressed in this paper is illustrated by figure 1. The left part shows the whole set of segments constructed from the sensor range data collected by a mobile robot during an experiment where the robot moved within the lab. One can note in the figure that many segments are duplicated and seem as shifted and twisted. This is the consequence of the dead-reckoning error accumulated by the robot during its displacements. The aim of this work is to be able of incrementally constructing a topological model of the map, such as the one depicted at the right part of the figure.

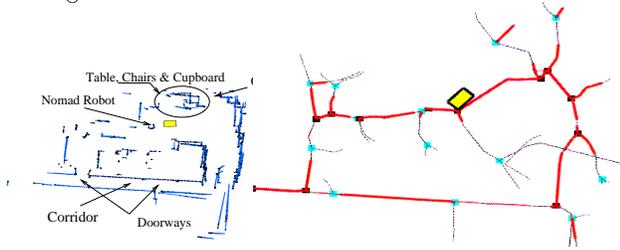


Figure 1: Topological map built in a real environment

The approach is based on the assumption that the explored world can be reliably modeled by segments obtained from a rangefinder performing an horizontal scan.

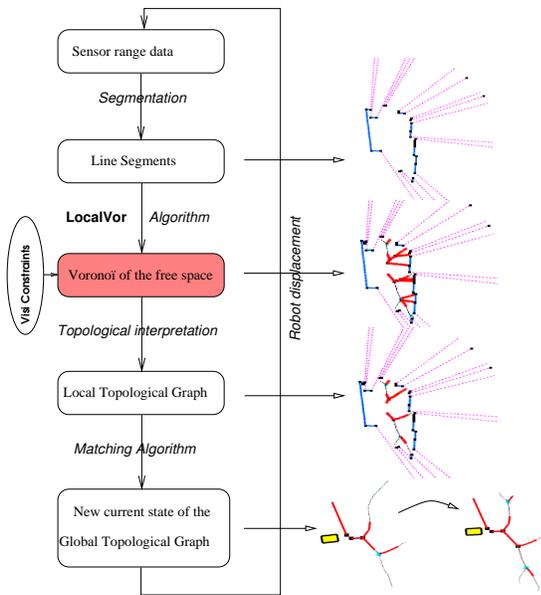


Figure 2: Approach

Figure 2 summarizes the scheme we adopted for topological modeling. As the robot is exploring the

environment, the system collects laser range data and build a sequence of segments representing the boundary of the perceived obstacles. Considering some visibility constraints, the Voronoï diagram of the local environment is built. A topological interpretation of this diagram is made before merging it to the current state of the global model. Then this sequence is repeated at the new position of the robot.

## 3 Local Topological Map

### 3.1 Local Perception

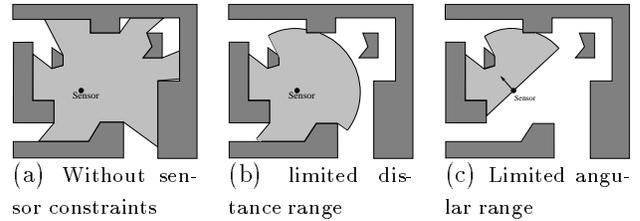


Figure 3: Effects of limited sensor ranges

We consider a laser sensor that has both limited distance and angular ranges (see Fig 3). Given a set of points collected by the sensor, a segmentation algorithm produces a sequence of possibly disconnected segments modeling the sensed obstacles. Discontinuities in the sequences of segments may be due to occlusions, specular limitation of the sensor (see Fig 4), or “unperfect” segmentation. By appending *escape-lines* departing from each discontinuity, we construct a generalized star-shaped visibility polygon which represents the current free space area perceived by the robot.

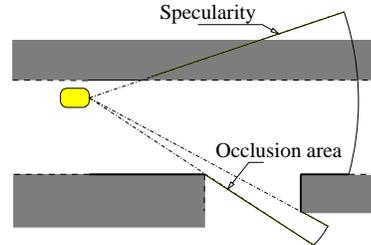


Figure 4: Escape-lines: Thick solid lines are the segments built from sensor data and thin solid lines are the escape-lines.

### 3.2 Local Voronoï Diagram

The Voronoï Diagram is a classical structure for path planning [1] defined by the set of points equidistant to at least two obstacles. Three-equidistant points correspond to possible bifurcations. Thus the

Voronoi Diagram provides a natural way to define a graph that explicitly captures the topology of the free space.

Considering the generalized visibility polygon as the free space area, we extract the local topology using an algorithm originally presented in [7]. The principle consists in tracing incrementally the Voronoi by moving a virtual point denoted  $R$ , initially placed at the sensor's position. An initialization step first computes the retraction of  $R$  onto the diagram. Successive steps computed based on the geometric analysis of the neighborhood of  $R$  (vertices on the boundary, nearest obstacles...) trace the current edge until  $R$  reaches a 3-equidistant point. A node is created at this position, with departing edges. The algorithm then selects one unexplored edge of the new node and continues tracing. It terminates when all the edges have been explored.

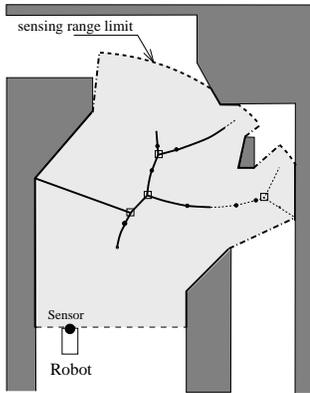


Figure 5: Local Voronoi graph. The graph drawn with thick solid lines represents the definitive part of the local model, while dashed edges are based on escape-lines and are only temporary. Empty squares are placed over each node.

As illustrated by Fig 5, each of the portions of the edges is labeled as *definitive* (if based only on boundary segments) or *temporary* (when at least one escape-line is involved). When one temporary portion intersects with another edge, the corresponding node is also labeled as temporary. Temporary nodes are likely to drift around their current position inside a *presence-area*. This area can be over-estimated by a circular region defined by the extremal positions of the implicated escape-lines (see Fig.6). This area will eventually contain at least one definitive node.

### 3.3 Structure of the Local Map

Mainly because of unperfect (noisy) data segmentation, this rough graph must be filtered to keep the

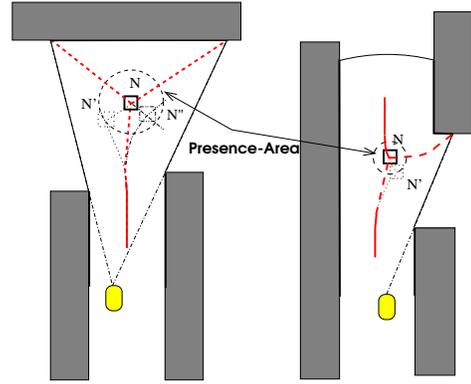


Figure 6: Presence area for one node:  $N'$  and  $N''$  are the equivalent position of the node  $N$  without considering each of the two escape-lines.

useful edges for navigation. In particular we discard the edges based on too flat concave vertices or due to narrow passages that do not allow the robot to navigate.

Nodes of the graph are described by their uncertain position (because of the uncertain position of the robot), the anticlockwise ordered set of edges emanating from them (see Fig 7) indexed with relative departing angles, a temporary/definitive attribute, and a confidence degree that reflects the persistence of the node along the successive local views (see next section).

Each of the edges is described by a sequence of portions. A portion is either a straight or curve segment which has an approximate length. It is also assigned a temporary/definitive attribute and distance to the environment is stored for each extremity. Global attributes of the entire edge can be derived from a simple integration of the local attributes of the successive portions.

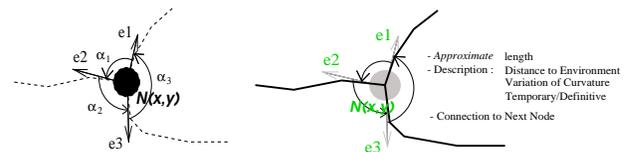


Figure 7: Topological Node

## 4 Global Topological Map

At each step of the exploration, the system gets the topology of the nearby environment. We assume that we can get a retraction of the robot position onto the graph and determine which is the direction of displace-

ments on the corresponding edge. Consequently, we naturally use the local graph to locally update the ongoing part of the current global graph.

Moreover, considering small displacements, we expect that an important part of the local graph will remain qualitatively identical over successive views. However, temporary nodes will have slightly changed and some nodes may have appeared or disappeared, as illustrated in figure 8. The figure shows the local graph constructed at two close positions of the robot. In the right figure, the specular phenomenon present in the left one has disappeared so that two new nodes can be modeled, while one node already present in the left figure has turned from temporary to definitive.

We next describe a procedure allowing to identify these local changes. Then we address the issue of loop detection to handle situations where the robot discovers again a previously modeled region of the environment.

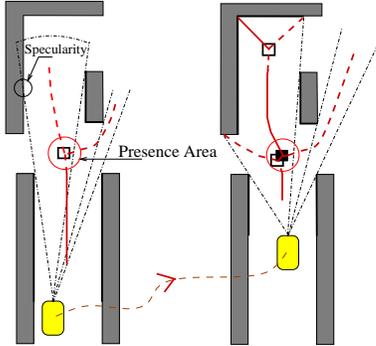


Figure 8: Local evolution: filled black squares represent definitive nodes whereas empty squares denote temporary nodes. From the left to the right figure the specularity disappeared and a new node is created lying inside the presence area of an existing node

#### 4.1 Local Growth of the Global graph

The point is to determine, for each node  $N_l$  of the local graph if it is already modeled in the global graph or not. The key idea is that the topological feature represented by  $N_l$  in the local graph is already modeled in the global one if we can reach a node  $N_g$  in the global graph by mean of a path topologically equivalent to the one that leads to  $N_l$  in the local graph.

This *accessibility procedure* works as follows. Note  $D$  the closer extremity of the local graph to the robot position. We construct a path from  $D$  to  $N_l$  as a set of nodes  $\{L_i\}$  to be traversed. Now examine this path “node-by-node”. To switch from one node  $L_i$  to the next, we define manoeuvres. Arriving at

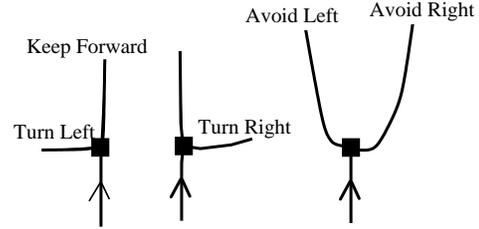


Figure 9: Manoeuvres arriving at a node

one node, the robot can either KEEP\_FORWARD (KF), TURN\_RIGHT (TR), TURN\_LEFT (TL), AVOID\_RIGHT (AR) or AVOID\_LEFT (AL) (see figure 9). Note  $D'$  the retraction of  $D$  onto the global graph. Starting from  $D'$  we examine the first encountered node  $G_0$  and compare it with the first local node  $L_0$ . For the equivalence to be acceptable, both nodes  $L_0$  and  $G_0$  must offer compatible manoeuvres.

Continuing this accessibility procedure for each  $L_i$  leads to one of the following situations :

- Both  $N_l$  and a corresponding global node  $N_g$  are reached. Then  $N_l$  is used to update  $N_g$ 's description, and  $N_g$ 's confidence degree is increased (eg. nodes  $L_2$  and  $L_3$  of fig 10).
- $N_l$  is reached but a still pending edge of the global graph has been reached.  $N_l$  is connected to this edge with a default value of the confidence degree (eg. node  $L_4$ ).
- $N_l$  is situated before the *presence area* of the corresponding node reached in the global graph. This can occur when the perceptual situation has changed so that a new node is discovered.  $N_l$  is inserted in the global graph with a default confidence degree (eg. node  $L_1$ ).
- One  $L_i$  lies after the *presence area* of the reached global node  $G_i$ . Then we determine if it is consistent with the new robot position, in particular considering possible occlusions and specularity. If it is, the accessibility procedure continues without updating anything; if not, the confidence degree of  $G_i$  is decreased and a copy of  $G_i$  is inserted in the local graph to allow continuing the procedure.
- $N_l$  stands inside the *presence area* of the reached global node  $G_i$ , but they have different topologies. This is possible only if  $G_i$  is constructed over escape-lines that have strongly evolved in the local perception (see fig 8).  $N_l$  is inserted but with a low degree of confidence if it is not the case.



nor 3 (because none of these nodes is connected to a node such as node 9).

When a loop has been identified, we make a systematic comparison between each encountered node respectively in the old and new part of the hypothesis, backtracking from the last node of the hypothesis until the end of the revisited region is detected. Then the loop is connected erasing the revisited part of the model, and the robot position is corrected.

## 5 Experimental Results

We performed some experiments using our robot Hilaré2 as a mobile sensor to collect laser range data. The robot was manually driven across the lab and the segmented data were stored every 20 cm. The figures below detail some steps of the construction of the topological graph shown in Fig. 1.

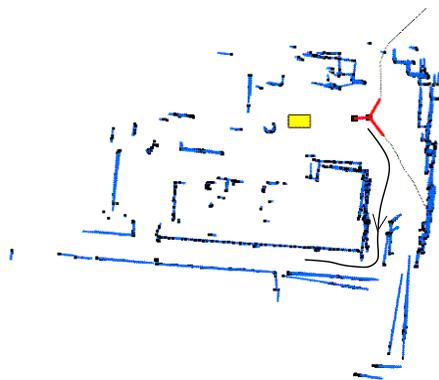


Figure 13: Experiment: The whole set of sensed segments and the first filtered local graph

The dimensions of the environment explored during this experiment are about  $20 \times 10$  meters and the topological graph of Fig. 1 contains 22 nodes (10 of them are definitive nodes). The initial state of the global graph (corresponding to the first local graph) is shown in Fig. 13. This local graph was obtained after filtering of the graph displayed in Fig. 14.

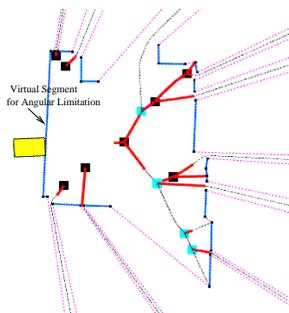


Figure 14: First local graph before filtering

Figure 15 shows a few steps of the incremental construction corresponding to the piece of path displayed in Fig 13.

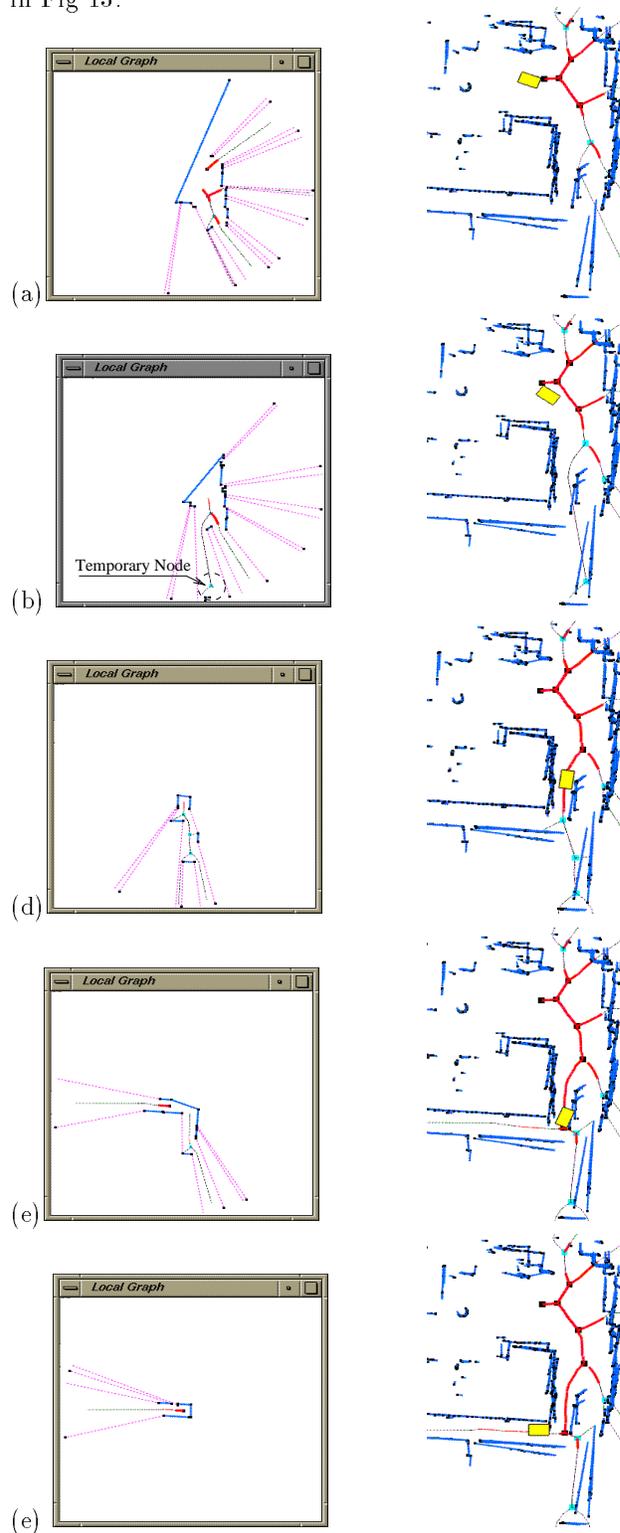


Figure 15: A few steps of the global construction

For each step, the left part corresponds to the local graph displayed with the local data (thick solid lines are the boundary segments and thin dashed lines are the escape-lines). The right part of the figure shows the new global graph after graph matching. Black squares denote definitive nodes whereas grey ones are only temporary. Thick solid lines are definitive edges of the graph and thin dashed ones represent temporary portions.

Each of the local view contains an average of 20 segments in a room-like neighborhood, and less than 10 segments in a corridor. In the first case the average computation time of the local graph is about 0.5s. In the corridor case, the local graph is obtained after less than 20ms.

One can also note over the successive steps that the global graph is roughly divided into a definitive and a temporary part. Recently discovered nodes are often temporary but they are updated in further exploration so that the temporary part of the global graph tends to converge towards the real skeleton of the environment. Note in figure (b) that because of occlusions and specularities, the local graph only builds a “very temporary” node (at the bottom of the figure), whereas figure (c) shows that the following steps allowed modeling more nodes. Figure (d) explicitly shows that the local graph may not be connex. The last figure (e) corresponds to the robot entering a corridor. Note that despite a quite large sensing range (over 10 meters) the local model (side walls) remains rather limited because of specularities.

## 6 Future Work and Conclusion

We have developed a new approach for directly constructing a topological model of an indoor structured environment from local range data. The model is obtained incrementally by merging each local topological graph with the current state of the model. Some encouraging results have been obtained on a real environment and we are currently validating the loop detection scheme.

Future work will concentrate on extracting exploration and navigation strategies, and also on demonstrating the robustness of the approach for long range navigation.

## References

- [1] J.C Latombe. *Robot Motion Planning*. Kluwer Academic Publishers, 1991.
- [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] J.J. Leonard and H.F. Durrant-Whyte. Mobile robot localization by tracking geometric beacons. In *IEEE Trans. on Robotics and Automation*, 7(3):376-382, 1991.
- [4] M.Khatib and R. Chatila. An extended potential field approach for mobile robot sensor-based motions. In *Intelligent Autonomous System*, Karlsruhe (Germany), 1995.
- [5] E. Rimon. Sensor Based Navigation of Mobile Robot. *The Eighth International Symposium of Robotics Research*, Hayama (Japan), 1997.
- [6] B. Bouilly, T.Simeon, R. Alami. A numerical technique for planning motion strategies for a mobile robot in presence of uncertainties. In *IEEE International Conference on Robotics and Automation*, Nagoya (Japan), 1995.
- [7] D.Van Zwynsvoorde, T.Simeon, R.Alami. An algorithm for incrementally constructing a topological graph for long range navigation, (in french), in *RFA 2000*, Paris, (France), 2000.
- [8] K. Nagatani, H. Choset, S.Thrun. Towards Exact Localization without Explicit Localization with the Generalized Voronoï Graph. In *IEEE International Conference on Robotics and Automation*, Leuven (Belgium), 1998.
- [9] K. Nagatani, H. Choset. Toward Robust Sensor Based Exploration by Constructing Reduced Generalized Voronoï Graph. In *International Conference on Intelligent Robots and Systems*, Kyongju (Korea), 1999.
- [10] B. Kuipers, Y.T. Byan. A robot Exploration and Mapping Strategy Based on a Semantic Hierarchy of Spatial Representations. *Journal of Robotics and Autonomous Systems*, 8:47-63, 1991.
- [11] S. Simhon, G. Dudek. A global topological Map formed by Local Metric Maps. In *International Conference on Intelligent Robots and Systems*, Victoria (Canada), 1998.
- [12] H. Bulata, M. Devy. Incremental Construction of a Landmark based and topological Model of Indoor Environments by a mobile Robot. In *IEEE International Conference on Robotics and Automation*, West Lafayette (USA), 1996.
- [13] S. Thrun. Learning metric-topological maps for indoor mobile robot navigation. In *AI Journal 99(1)*, 1998, pp. 21-71.
- [14] R. Simmons, S. Koenig. Probabilistic Robot Navigation in Partially Observable Environments. In *International Joint Conference on Artificial Intelligence*, 1995.