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A HYBRID PATH PLANNING TECHNIQUE FOR PARTIALLY UNKNOWN INDOOR ENVIRONMENTS

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ABSTRACT—This paper presents an exploration algorithm for partially or totally unknown environments. The method is based on a representation that integrates metric and topological paradigms. The metric paradigm produces an accurate representation of the environment. The topological map is built over the metric map by means of a hierarchical structure. It reduces the metric data volume and can be processed in a more efficient way. The representation of the environment is used to calculate a route through unexplored areas. The main advantage of the proposed scheme is that it can operate in known and unknown areas in a fast and efficient way.

Key Words: Mobile robot, exploration, metric paradigm, topological paradigm, indoor environment.

1. INTRODUCTION

One of the main concerns of modern robotics is efficient exploration of totally or partially unknown indoor environments. Exploration may rely on several strategies, using or not using *a priori* knowledge of the environment. Some strategies rely on an off-line calculation of the path to follow. Colegrave and Branch [6] specifically provide a route the agent must follow. However, this method can not deal with moving obstacles. Hofner and Schmidt [10] assume the knowledge of a two dimensional map that works when the covered area is free of obstacles. Zelinsky *et al* [17] suggest a technique based upon an extension of the distance transform for planning paths that can not handle moving obstacles. Finally, Choset *et al* [5] propose a method that can only deal with polygonal obstacles. There are also some approaches when there is not an *a priori* knowledge. VanderHeide and Rao [15] suggest a method for indoor environments, that lacks in dealing with cluttered and unstructured environments. Butler *et al* [4] propose a method that just works for rectilinear environments.

To explore an environment in an efficient way, we need to learn about its structure. This knowledge is used to build a representation. The two main approaches to representing and modelling indoor environments are the metric and topological paradigms [1] [13]. Metric approaches [7] aim at representing the features of the world in an accurate way. These maps are easy to construct and to update. Their geometry corresponds directly to the geometry of the represented environment. Hence, they provide information about the relations among different places, even if those places are still unexplored. Metric maps are vulnerable to errors affecting metric information and they may yield a huge data volume to represent medium sized environments at adequate resolutions. On the other hand, topological approaches [11] represent the environment by means of graphs. Nodes in the graph represent distinctive regions of the environment and arcs represent the spatial relationships between them. Topological maps are more compact than metric ones, allowing a more efficient use of computational resources.

In order to combine the advantages of metric and topological paradigms, some map building techniques rely on integrating both paradigms [1] [8] [11] [13]. Arleo *et al* [1] obtain a variable resolution partitioning from an occupancy grid. They model obstacle boundaries by means of straight lines. The main drawback is that they can not deal with irregular shape regions nor with walls which are not parallel or orthogonal. Fabrizi and Saffiotti [8] propose a topological representation extracted from the metric map. The topological map is constructed with information about free space. Thus, unexplored regions are not represented in the topological map. The third approach [11] consists of building a topological map where each node has geometrical information of the place where it was inserted, allowing the inference of geometrical relations between nodes. However, these operations must usually be performed off-line because they are slow and computational expensive. Finally, Thrun [13] splits free space into homogeneous regions according to region shape criteria. However, his topological map is constructed off-line and only when a fully explored metric map is available.

This paper presents a technique for efficient exploration of partially or totally unknown environments. To that purpose, we propose a new representation where topological information is easily grounded at metric level on-line. When the representation is available, unexplored nodes at topological level are disposed to be visited in an efficient order. Then, a path between all those nodes is calculated. Section 2 presents the problem of topological map building. Section 3 shows a planning technique to visit all unexplored states. Section 4 presents some experiments and results. Finally, conclusions and future work are shown in Section 5.

2. TOPOLOGICAL MAP BUILDING

The principle of topological maps is to split free space of the real environment into a small number of regions. These regions have different sizes and they present an homogeneous probability of occupation. In this paper, metric and topological paradigms for modeling indoor environments are integrated for map learning.

2.1 Foveal non-uniform resolution grids

Grid decomposition is one of the most popular metric representation techniques. It consist of decomposing the environment into a lattice of square-shape cells. Obviously, the computational efficiency of an exploration algorithm relying on grids depends on the fineness of the decomposition. However, the time complexity of those algorithms increases exponentially with the degree of decomposition. One solution to solve this problem is to work in non-uniformly decomposed grids [14]. The main disadvantage of methods based on non-uniformly decomposed grids is that it is not easy to achieve an optimal decomposition.

A fast and easy way of decomposing the environment into a non-uniform grid can be achieved by using foveal geometries. These geometries are typically used in computer vision, particularly in active vision, in order to build real time perception systems. They present a centred high resolution area known as fovea and a progressively decreasing resolution towards the peripheral regions. This changing resolution profile can be achieved by using a cartesian-exponential sampling strategy [2], which is defined by two parameters: the number of resolution rings of the grid, and the subdivision factor or number of subrings in each resolution ring. Figure 1.a and b present, respectively, an uniform resolution probabilistic map and a cartesian-exponential map where the number of resolution rings is equal to 2 and the subdivision factor is equal to 2.

2.2 Foveal polygon

The value of a given cell of a probabilistic map provides its probability of occupation. In uniform grids, the cell location in the environment is implicitly represented by its position in the grid, but in non-uniform grids, additional information about the size and shape of the area associated to each node is required. A hierarchical structure for representing and processing foveal data known as foveal polygon was proposed in [2]. Lower levels of the polygon present a progressively larger area of the map at decreasing uniform resolution. The first level of the polygon presenting the whole map is known as waist level. If further data reduction is desired, the structure allows the creation of more levels presenting the whole map at decreasing resolution above the waist. These last levels above the waist conform a classic hierarchical structure known as pyramid. Figure 1.c presents a typical foveal polygon built over a map yielding three different resolutions. It can be noted that any level i below the waist presents the portion of the map surrounded by ring i at the resolution of this ring. The foveal polygon in Figure 1.c is composed of three

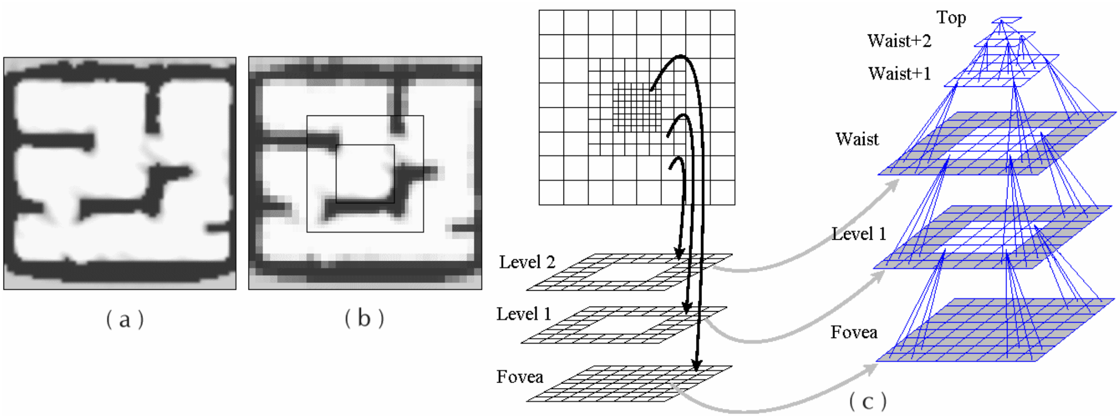

Figure 1. Foveal polygon: (a) uniform resolution probabilistic map; (b) foveal non-uniform resolution probabilistic map; (c) foveal polygon structure.

levels of resolution -corresponding to the three resolutions in the map- from the fovea to the waist plus a four level pyramidal structure over the waist.

To construct the foveal polygon we have to generate the levels of resolution below the waist and the pyramidal structure above it. Firstly, in order to build a node *n(i,j,k)* at level *k* below the waist, being the fovea the level 0, the probability of the set of 2x2 nodes immediately below it at level *k-1* is averaged. The computed node is known as parent and it is linked to those who were used to generate it, which are known as sons. After all nodes at level *k* have been calculated, the level presents the same resolution that ring *k*, which can be therefore appended to the generated nodes in order to present a larger area of the map. When the levels of resolution have been constructed we build the pyramidal structure above the waist. This paper uses a 4-to-1 pyramid, where each of its levels has 1/4 of the nodes of the level immediately below. The pyramid is built following the steps:

1) Let *k=waist*.
2) Average the probability of each set of 2x2 nodes *n(i,j,k)* at level *k* to generate a single node (parent) at level *k+1*.
3) Create a link between each of the 2x2 nodes and their parent. Thus, computed nodes are linked to those that were used to generate them.
4) Let *k=k+1*. Return to step 2 until level *k* yields a single node.

The proposed structure allows progressive abstraction of information within the hierarchy. Algorithms can work at any level. The polygon resembles a typical vision hierarchical structure known as pyramid, which may be considered as a special case of the polygon where the fovea covers the whole map. However, generation of a foveal polygon is faster than that of a pyramid and the structure can be more efficiently stored.

2.3 Adaptive linking procedure

After a foveal polygon is built, several versions of the map at progressively lower resolutions are available. However, regions at the metric map associated to the nodes of the foveal polygon do not present an homogeneous value of probability of occupation. In order to assign an homogeneous region of the environment to each polygon node, links between levels of the foveal polygon are redefined by using an iterative procedure known as adaptive link principle [3]. The process consists of rearranging links between nodes at different levels in a controlled way. The method is performed following the steps:

1) Let k=1.
2) For each node n(i,j,k), find the most similar parent at level k+1 in a 2x2 vicinity above the node and establish a link between them. Each son must only have one parent but a parent may have from zero to 16 sons.
3) Regenerate level k+1 using the new links. Each father is recomputed using the average of the sons linked to it. If any change occurs, return to step 2. Otherwise, the level is stabilized.
4) Let k=k+1. Return to step 2 until the whole structure is stabilized.

When the process finishes, each node of the structure is linked to an homogeneous region at the base. Free space, obstacles and unexplored regions will be grouped in a set of nodes as reduced as possible. When the structure is stabilized, it keeps the topological information by the set of links. Figure 2 presents different levels of the structure when the adaptive link principle has not been applied (Figures 2.a, b and c), and when it has been applied (Figures 2.e, f and g). Free space is in white color, obstacles are in black color and unexplored regions are in gray color. The pyramid structure has a set of different resolution maps. When the adaptive linking procedure is not applied, the resultant levels are not useful, because cells at level k+1 are just obtained averaging cells at level k. The adaptive link principle overcomes this problem, as it is shown in Figure 2. Each node is now linked to an homogeneous and irregular shape region at the base.

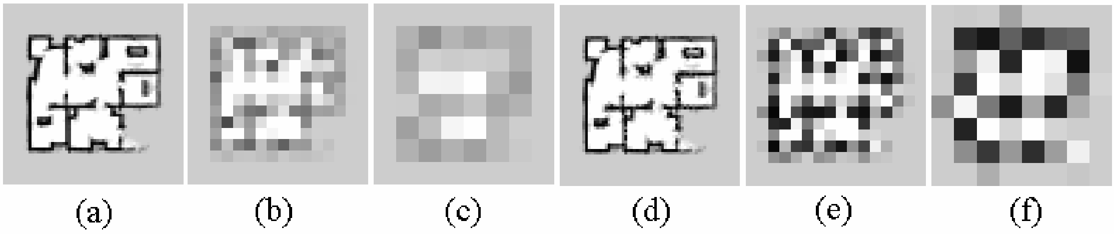

Figure 2. Different levels without adaptive linking procedure: (a) waist of 64x64 nodes; (b) level of 16x16 nodes; (c) level of 8x8 nodes. Different levels with adaptive linking procedure: (d) waist of 64x64 nodes; (e) level of 16x16 nodes; (f) level of 8x8 nodes.

2.4 Topological map building

In order to build the topological map, a working level *L* of the foveal polygon is selected. Nodes at the working level divide the environment into a set of homogeneous regions. The topological map consists of nodes at the working level corresponding to free and unexplored space and the spatial relationships between them. Obstacles are not represented in the topological approach because the robot can not pass through these regions.

When the working level is selected, we analyze the structure to obtain the spatial relationships between nodes. If two nodes are connected, there is and arc between them in the topological map. The projection of these nodes over the metric map generates a connection graph. This graph and nodes at the working level constitute the topological map. Figure 3 shows a topological-metrical map. Figure 3.a presents the base metric map. Figures 3.b and d presents two working levels of 8x8 and 16x16 nodes, respectively. Finally, Figures 3.c and e show the connection graphs generated by the working levels of Figures 3.b and d, respectively. The higher the number of nodes of the working level, the more complex the topological map is, and the time required to build it. However, the representation of the environment is more reliable. One of the main advantages of the topological map is that unexplored regions are implicitly represented. Therefore, the graph will allow to intelligently explore the environment, moving across those unexplored regions at the same time as the robot explores them.

3. INTELLIGENT EXPLORATION

The proposed metric and topological approach explicitly represents unexplored areas. The topological level presents nodes related to explored and unexplored regions, and geometric relations between them are represented at metric level. Also, the proposed map can be constructed on-line. Hence, the map can easily be updated while the robot navigates through unknown areas. Exploration of a totally or partially unknown environment relying on the proposed map can be reduced to the following facts:

1) There is a set of polygon nodes whose occupancy value is equal to 0.5, which are related to unexplored regions.

2) The robot must visit each of those nodes only once.

3) It is desirable to choose an efficient trajectory to travel from node to node, so that the total traveled distance is as reduced as possible.

The navigation technique is based on a two level approach. First, a high level route to visit all unexplored areas is calculated at topological level. Since the topological map presents a reduced number of

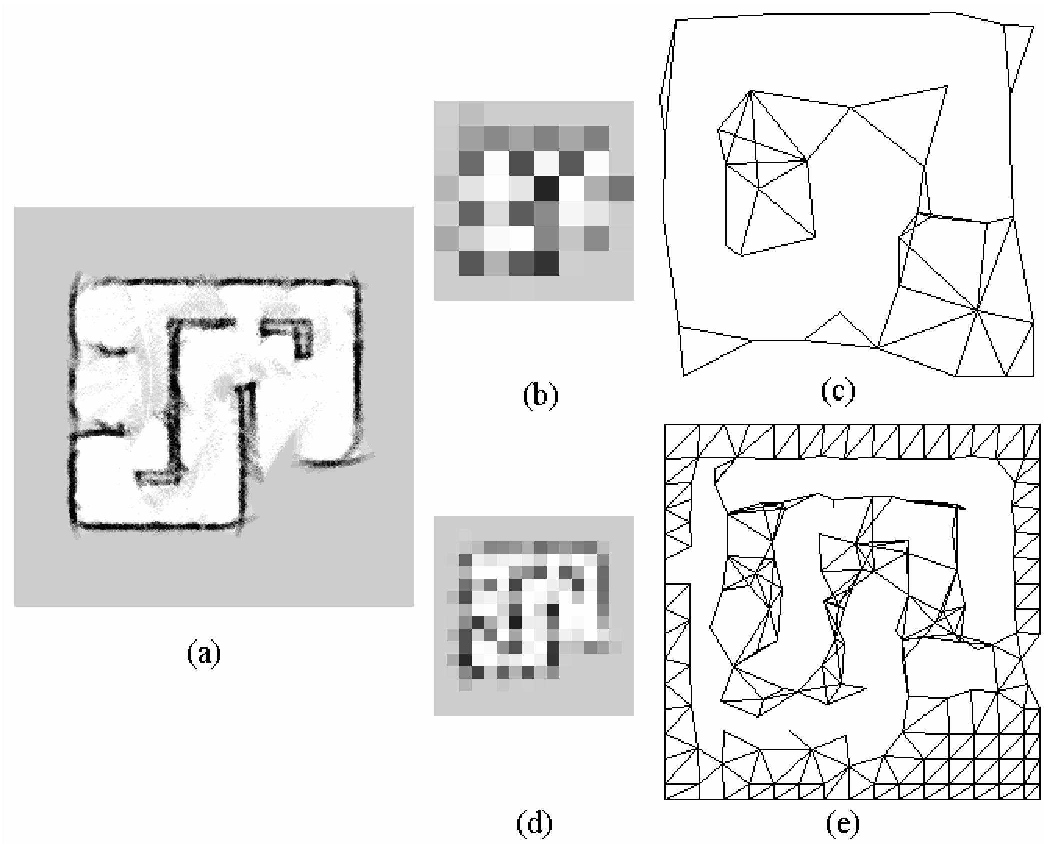

Figure 3. (a) Metric map of 256x256 nodes; (b) working level of 8x8 nodes; (c) topological map for (b); (d) working level of 16x16 nodes; (e) topological map for (d).

nodes, this calculation is not too computationally expensive. Then, we plan a trajectory at metric level joining all unexplored nodes in the calculated order. This low level planning is based on a potential field approach, so it is computationally cheap [16].

3.1 High level planning

The exploration algorithm must firstly select the set of unexplored regions. In our case, these regions are associated to the polygon nodes at the working level whose probability of occupation is equal to 0.5. The relationship between nodes at the working level and nodes at the base is explicitly kept by means of the link set obtained after the adaptive link principle has been applied. Thus, we know the irregular shape region at the base each node of the working level is linked to. Furthermore, due to the process of obtaining regions, we do not need to make any hypothesis about obstacles shape. Then, the method needs to obtain distances between these unexplored regions. In order to speed up this step of the algorithm, we assume that every region is represented by its centroid. The centroid is the centre of mass of the region. If two regions are connected, the distance between them is the euclidean distance between their centroids. If they are not connected, the distance between them is set to infinite.

When we have the set of unexplored nodes, the problem is equivalent to the traveling salesman problem (TSP), a classic NP-complete problem. The TSP consists of, given a set of nodes $N=\{c_1, c_2, ..., c_n\}$ and a distance $d(c_i,c_j)$ for each pair of nodes, searching for a tour of all the nodes presenting a minimum length. Since the TSP is a well known problem, several methods to solve it have been suggested. If the number of nodes is small we use an exhaustive search to find the optimal solution. If the number of nodes increases, it is too computationally expensive to find the optimal solution. Thus, it would be desirable to find an algorithm that gives a solution at a lower computational cost, even if it is suboptimal. The TSP has been traditionally used as a neural network benchmark, but its validity for this particular problem has been widely questioned [9]. Consequently, this paper relies on a genetic approach [12]. The TSP solving algorithm returns an ordered list of nodes, C, to visit. However, it must be noted that there is still no valid path between each two nodes, because arcs between nodes only represent those nodes linked to connected regions.

Figure 4 shows a route calculated by the TSP solving algorithm. The topological map is overimposed to its corresponding metric map, which is only partially explored. This topological map presents 12 nodes, including 8 unexplored ones and 4 explored ones. If the robot can travel between two regions, their corresponding nodes are linked with and arc. Nodes to be visited are marked with a black circle. Nodes that do not belong to the set of unexplored regions are marked with an empty circle. The route starts and finishes at the node labeled START. Nodes to be visited are numbered from 1 to 8 in an ordered way according to the solution of the TSP at high level.

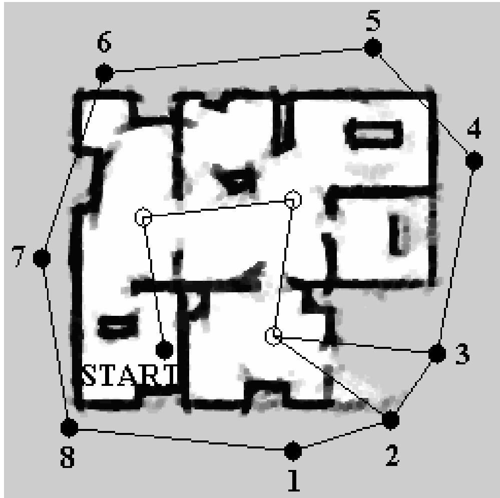

Figure 4. High level route planning for a partially unknown environment.

The resultant route does not seem to be optimal. However, this is not true because the TSP algorithm obtains, in this case, the optimal route for the distance matrix between unexplored regions provided by the previous stage. Although the TSP solving algorithm returns the optimal route, the process is influenced by the relationships between regions because the distance matrix is determined by the connectivity between regions. Also, the TSP algorithm returns a sequence of nodes, but it is not concerned about how to travel among them. It is important to note that the final path is calculated at metric level by a low level planner, as described in next section.

3.2 Low level planning

Although the TSP solving algorithm returns an ordered list of nodes, C, to visit, it is necessary to calculate a path between each consecutive node in C. These paths are calculated by the low level planner. Our method is based on a potential field approach [16]. For each pair of regions we have to implement the following steps:

1) Computation of the skeleton of free space. The skeleton extraction relies on calculating a map of distance to obstacles.

2) Generation of the potential field V of the skeleton of free space.

3) Generation of the potential field for the rest of the metric map.

4) Path tracking relying on the resulting potential field. When the potential field is available, the robot can move from the departure to the arrival point by following a path of minimum potential.

Figure 5.a presents a metric map yielding the departure and arrival points of a single path. Figure 5.b shows the map of distance to obstacles for the metric map in Figure 5.a. And Figure 5.c shows the extracted skeleton from the map in Figure 5.b. Finally, Figure 5.d shows the potential field generated for the metric map in Figure 5.a and the path the robot would track overimposed in black.

Finally, we present in Figure 6 the complete path to efficiently explore a partially unknown environment. The path is overimposed to its metric map of 256x256 cells. The region where the robot is into must be included as a node to visit, even if it is an explored region, because the route starts and finishes at it. The robot is at the node labeled START. Figure 6 presents the unexplored nodes obtained with the algorithm when the working level is 4x4. Nodes to be visited are numbered from 1 to 8 in an ordered way according to the solution of the TSP at high level (Figure 6). It is important to note that the low level planning is concerned about how to travel between unexplored nodes.

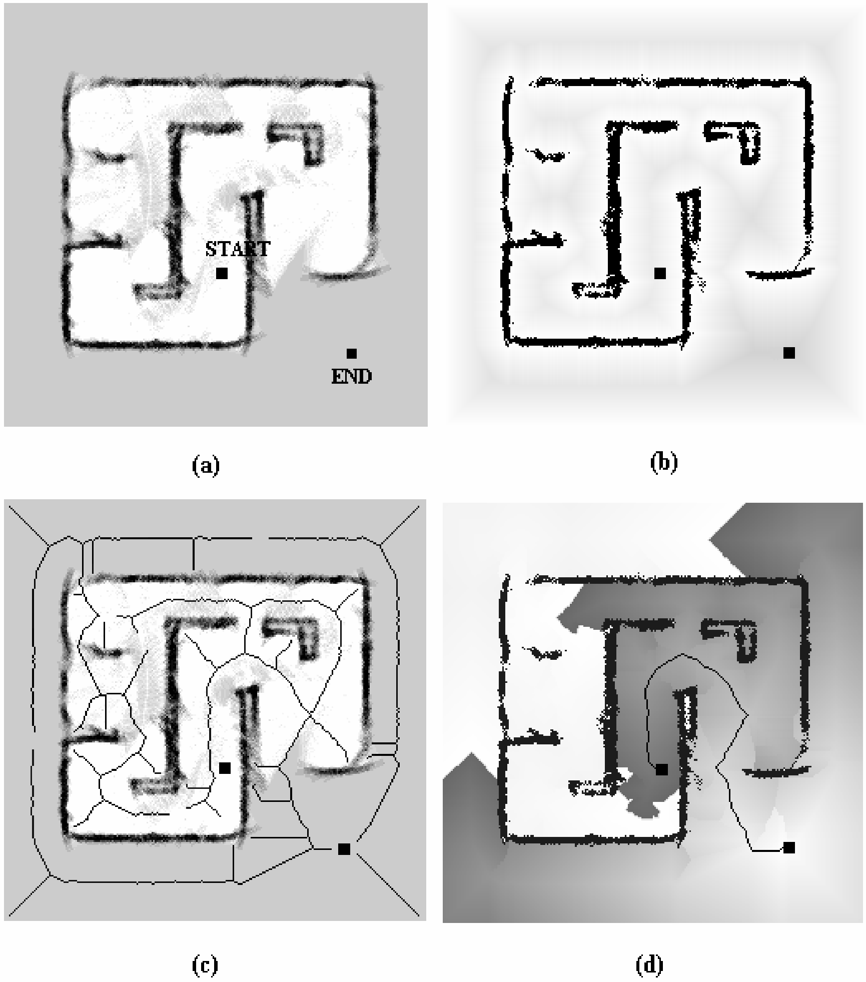

Figure 5. Low level planning based on potential fields: (a) departure and arrival point over the metric map; (b) map of distance to obstacles; (c) skeleton of map (b); (d) potential field for (a) and resulting path.

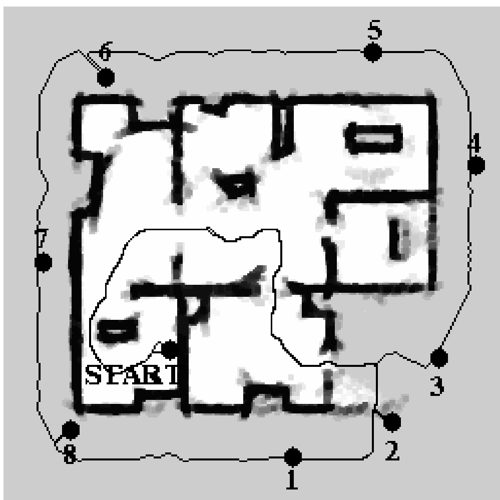

Figure 6. Low level route planning for a partially unknown environment.

4. EXPERIMENTS AND RESULTS

The proposed technique has been tested for different environments, totally or partially unexplored. The system has been implemented on a Nomad 200 robot. The robot is connected via radio to a Pentium III 700 MHz with 128 Mbytes RAM. This PC supports the whole algorithm.

Figure 7 shows an environment with a maximum size of 17.2x8.2 m^2.The environment has an irregular shape, where we can find columns, metallic cupboards and boxes of cardboard and wood (Figure 7.a). In order to achieve a suitable decomposition degree at metric level, the environment in Figure 7 has been represented by using a grid of 256x256 cells (Figure 7.b), where the position of the robot is labeled START. The working level has 4x4 nodes (Figure 7.c). The position of the robot corresponds to the node marked with a black cross. Finally, Figure 7.d shows the path after applying the proposed algorithm. The number of unexplored nodes is seven, including the one the robot is into. It can be noted that, with a small working level of 4x4 nodes, the calculated path covers all the unknown regions of the metric map, allowing the robot to explore the whole environment. It is important to notice that the algorithm only consumes 0.9 s.

The proposed exploration technique calculates possible paths in unexplored regions to reach all unexplored nodes. However, most times there are obstacles in unexplored areas. Thus, while the robot is following the route it will became unfeasible as soon as an obstacle appears in its way. In those situations it is necessary to rerun the algorithm so that the exploration technique provides a new route for the robot to reach all unexplored nodes according to the updated metric map. Since the whole calculation time of the planning algorithm is lower than one second, the robot does not need to stop when it detects an obstacle in its route.

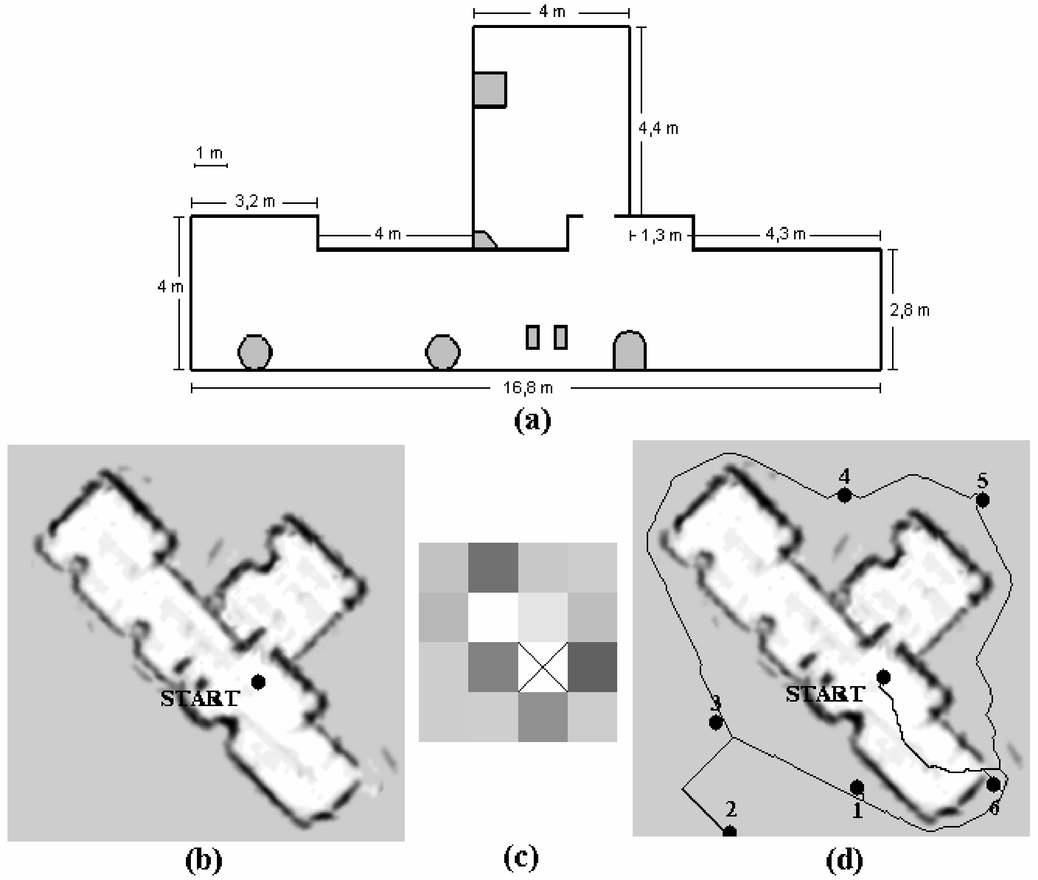

Figure 7. Real environment: (a) sight of the environment; (b) metric map of 256x256 cells; (c) working level of 4x4 nodes; (d) complete path over the metric map.

It is also interesting to see the exploration process of an environment, as illustrated in Figure 8. Figure 8.a shows an environment with an area of 32.5x32.5 m^2. The environment has been simulated because there was no such a large environment in the laboratories where tests were performed. Nevertheless, tests in smaller real environments have also been satisfactory, as it is shown later. In order to achieve a suitable decomposition degree at metric level, the environment in Figure 8 has been represented with a grid of 256x256 cells.

Figures 8.b-8.j show the metric map at different stages of the exploration process. Initially, the environment is completely unexplored and it is assumed that there are no obstacles in it. Hence, the algorithm calculates a regular route to explore the whole environment. However, such a route will not be feasible as soon as an unexpected obstacle appears in the way of the robot. Each time the robot finds an unexpected obstacle in its way, we have to rerun the algorithm. Thus, the exploration technique computes a new valid route to explore the partially unknown environment according to the updated metric map. The exploration finishes when there are not unexplored nodes left in the map or it is impossible to reach these unexplored nodes from the actual position of the robot. It must be noted in Figure 8 that the proposed technique explores the totally unknown environment to provide a representation of it.

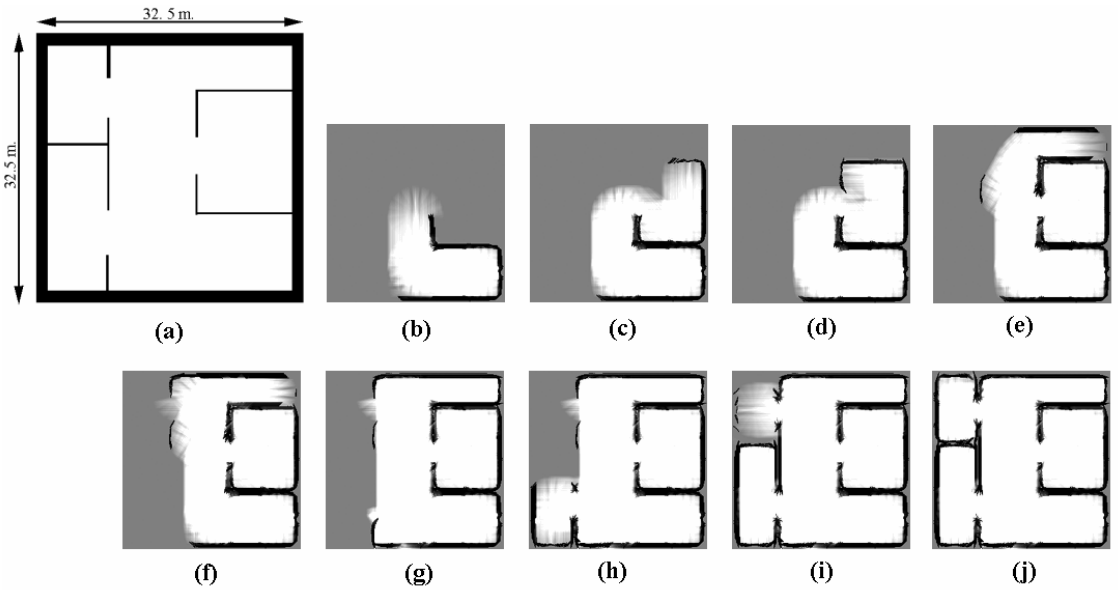

Figure 8. (a) Environment to be explored; (b) – (j) updated metric level of the environment of (a) at different stages of the exploration process.

Finally, we present a test performed in a laboratory. This real environment (Figure 9.a) has metallic cupboards, card boxes, chairs and tables. Hence, sonar readings are exposed to most typical errors. The environment has been represented by using a grid of 256x256 cells, where each cell had an area of 25 cm^2. As it is shown in Figure 9, the results are satisfactory, even with sonar errors. Figures 9.b-9.f show the metric map at different stages of the exploration process. The robot starts to explore on the left side of the laboratory heading east (Figure 9.a). As in the simulated environment (Figure 8), each time the robot detects and obstacle in its way, it changes its direction and runs the algorithm again. From its initial position, the robot firstly explores the down side of the laboratory, as is presented in Figure 9.c. After that, the method guides the robot to the upper side of the room. It can be noted that the robot has to walk through the left side (Figure 9.d) to get to the upper side (Figure 9.e). Thus, the only unexplored are of the laboratory is the right part of it. Then, the algorithm manages to explore this region and the exploration process finishes.

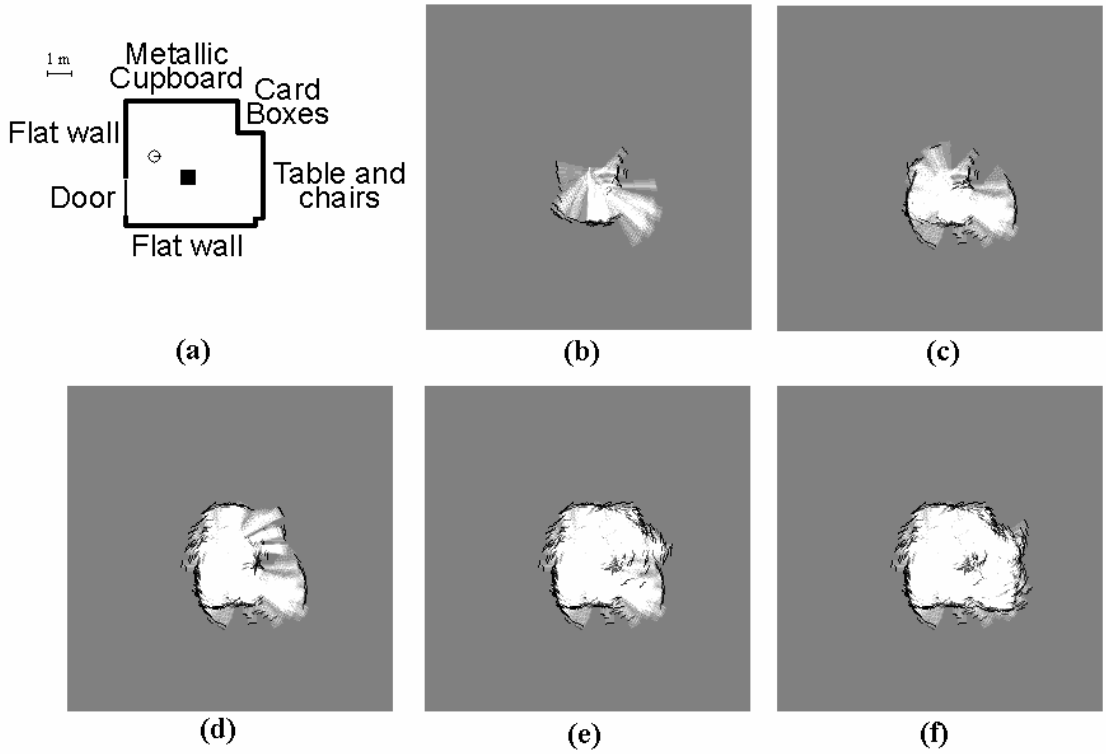

Figure 9. (a) Real test environment; (b) – (f) updated metric maps of the environment of (a) at different stages of the exploration process.

5. CONCLUSIONS

This paper has presented a strategy for efficient exploration of partially or totally unknown environments. One of the main novelties of this work is a new metric-topological map of the environment which allows explicit representation of both explored and unexplored areas at topological level. The main advantage of the proposed structure is that the relationship between its topological and metric levels is explicitly kept by means of a link set. When the representation is available, unexplored nodes at topological level are chosen to be visited in an efficient order. The method is fast enough to recalculate a route without stopping the robot when unexpected obstacles appear in unexplored areas. This method has been successfully tested in different dynamic indoor environments. Future work will focus on improving the data structure and dealing with moving obstacles by means of fast and efficient reactive tracking behaviors.

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