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Improving Robot Path Planning Efficiency with Probabilistic Virtual Environment Models

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Abstract - *Probabilistic multiresolution occupancy grid modeling has recently been developed to map both 2-D and 3-D cluttered spaces. These models can be used to provide an enhanced representation of the cluttering state of space in a robot workspace. As a result, they reveal to be promising tools to improve classical potential field based robot path planning strategies. These approaches rely on a combination of repulsive and attractive potential fields to attract the robot toward a given goal while ensuring safe distance from the obstacles. This paper proposes an new approach to directly compute repulsive and attractive potential fields from the probabilistic occupancy models without the need for distance tables or wave propagation. Experimentation revealed that multiresolution probabilistic models encoded as quadtrees or octrees significantly reduce processing time and speed up robot operation.*

Keywords - *Probabilistic occupancy modeling, potential fields, path planning, collision avoidance.*

I. INTRODUCTION

The extension to 3-D space of the probabilistic modeling paradigm introduced by Elfes [1] now allows to model 3-D cluttered spaces by means of multiresolution probabilistic occupancy grids and octrees computed from raw range images in a tractable manner. In opposition to discrete occupancy grids that only associate *empty* or *occupied* states to each region of space [2, 3], probabilistic occupancy grids or octrees associate an estimate of the occupancy probability ranked between 0.0 and 1.0 with each voxel. This provides a knowledge of the occupancy state that is more suitable for safe path planning as it allows to take into account sensor uncertainties and registration errors.

Significant improvements have also occurred in the development of discrete potential field based path planning techniques using occupancy models. Efficient strategies now allow to partially override the problem of local minima [4] that was previously accommodated using random and non-repetitive approaches [5, 6].

In this paper, the use of multiresolution probabilistic octree models for the direct computation of both the attractive and the repulsive potential fields is studied in the context of collision free path planning. Specific characteristics of probabilistic octrees are put to advantage to improve performances in potential field computation and reliability.

For instance, in probabilistic models, transitions between occupied and free areas of space are usually progressive due to the uncertainty on raw measurements. As the uncertainty tends to increase proportionally with the number of range data collected on the scene, the model dynamically adjusts its transition zones that tend to become smoother and wider. Such a behavior improves the reliability of the selected free paths ensuring that the robot stays sufficiently far away from obstacle boundaries. The safety level that can be achieved is beyond that of classical discrete occupancy models. The latter can only rely on predetermined and arbitrary security margins imposed all around obstacles to inflate them in order to compensate for measurement uncertainties but without a dynamic behavior.

Moreover, repulsive potential fields should typically exhibit a continuous progression from empty space (weak repulsion) to cluttered space (strong repulsion). Therefore, advantage can be taken of the smooth evolution of the occupancy probability to directly estimate the repulsive potential field from the occupancy probability without any intermediate computation. Apart from significantly reducing the computational workload of the robot path planner, this also leads to smoother movements of the robot along its trajectory.

Finally, the attractive potential field that guides the robot through free space can also be estimated directly from probabilistic occupancy models. As the probability of occupancy is encoded on a normalized analog scale (between 0.0 and 1.0) rather than by discrete states, the merge of contiguous regions of space having similar occupancy states becomes more suitable for error handling. This also allows to introduce additional selection criteria in the path planning algorithm that increase flexibility.

Following sections summarize the paradigm of probabilistic occupancy modeling and detail the computation of repulsive and attractive potential fields. Experimental results are presented to compare robot path planning based respectively on probabilistic virtual representations and discrete models.

II. PROBABILISTIC MODELING

The modeling framework selected for this research work is that of 2-D or 3-D occupancy grids that result from the recursive subdivision of space. However, each voxel is tagged with a state of occupancy comprised between 0.0 (*empty*) and 1.0 (*occupied*) for the area it encloses. Unknown or unmapped space is represented by a level of 0.5. For compactness, these occupancy grids are encoded in tree-like structures, quadtrees for 2-D space or octrees for 3-D space [7, 8].

Previous work allowed us to extend the original concept proposed by Elfes for 2-D space that relies on a Bayesian probabilistic approach [1, 9]. A new formalism of the Bayesian occupancy probability estimation has been proposed to circumvent the computational complexity that initially resulted from the addition of the third dimension [10]. Operating directly on raw range measurements, the proposed framework computes the occupancy probability of a given volume of 3-D space centered on the sensor viewpoint. This process is repeated for each viewpoint visited by the sensor. A set of local probabilistic occupancy grids whose origins correspond to each viewpoint is then generated. These local grids are finally merged into a global Cartesian grid by means of an exhaustive intersection search.

As a series of separate measurements are usually required to map an entire scene, important overlaps occur between the respective fields of view of the sensor. Initiating the modeling process on a perfectly unknown representation (0.5 everywhere) and relying on the redundant information provided by a laser range sensor, a Bayesian merge is applied to estimate an optimal value for the occupancy probability in a given area (a voxel). This procedure results in a progressive reinforcement (or decrease) of the occupancy probability as coherent (or contradictory) measurements are provided by the sensor. Figure 1b shows an example of such a probabilistic model for a typical scene made of a tubular structure. Gray shading corresponds to the probability of occupancy: white being 100% (*occupied*), and black 0% (*empty*). For clarity, only voxels having a probability of occupancy higher than 50% (*unknown*) are displayed.

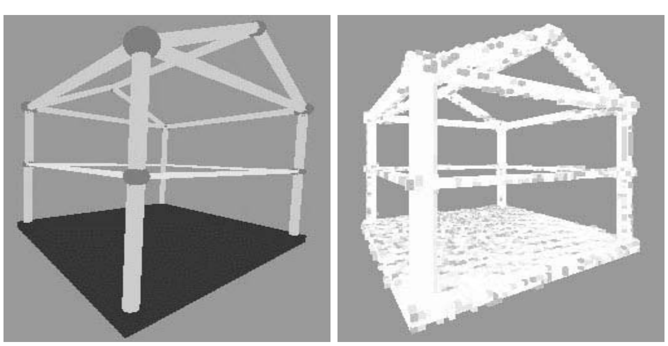

Fig. 1. a) A virtual representation of a 3-D scene around which a manipulator has to operate without collision and b) its probabilistic occupancy model.

III. POTENTIAL FIELDS

Once a probabilistic occupancy model of the robot workspace is available, this information can be used to directly compute a repulsive and an attractive potential field on which the path planning algorithm will rely to determine the safest trajectory for the robot to follow. The repulsive field ensures that the robot keeps a safe distance with respect to all obstacles while the attractive field pulls the robot or its end effector in the direction of the desired destination.

Classical path planning techniques try to identify sequences of empty voxels. Similar approaches can be used with probabilistic models except that the planner can now look for regions that are "sufficiently safe", that is, parts of the workspace that have a lower probability of occupancy than a preset threshold. Adjustments on this threshold make the path planning procedure more flexible to deal with situations where space to circulate is tight between objects.

A. Computing a Repulsive Potential Field

With discrete occupancy grids, a widely used scheme to build the repulsive potential field consists of computing a distance table from the nearest obstacle for each voxel in the grid [11, 4, 12]. Once this table is evaluated, the repulsive field is computed as being inversely proportional to the distance. Figure 2 shows the characteristic distribution of such a field computed from a distance table for a set of two obstacles in free space measured successively by a range sensor from their left and right sides respectively. With such a model, the uncertainty on the objects position and orientation must be dealt with by adding a sufficient, or even oversized, arbitrary security margin around each of the obstacles. Since the repulsive force inside this security margin must be set to a large value, it reduces the free space available for the robot to circulate. This situation can lead to a failure of the path planning task.

Probabilistic occupancy models alleviate some of the constraints of the original scheme. First, the repulsive potential field can be computed directly from the occupancy probability of a given cell. Since the occupancy probability progressively grows with the proximity of an obstacle, the repulsive potential field that is evaluated as a function of the probability occupancy exhibits the same behavior, which is desirable. Moreover, in opposition to classical techniques, potential field computation on probabilistic models is performed without the need for a distance table computed with respect to obstacle boundaries. This significantly contributes to reduce computing time.

Observing the typical probabilistic occupancy distribution following the modeling phase provides useful hints for the determination of a proper repulsive potential field function. Probabilistic occupancy models contain areas which are tagged with a *0.5* (*unknown*) occupancy probability. The

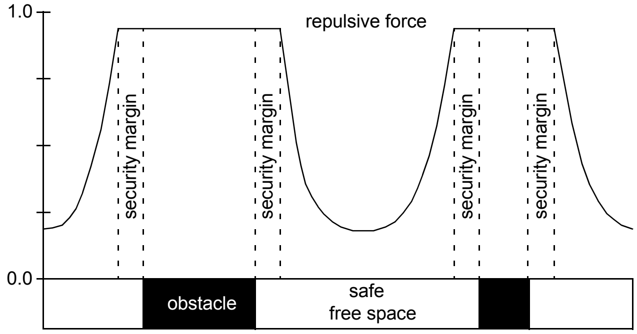

Fig. 2. Repulsive potential force computed from a discrete occupancy grid and a distance table.

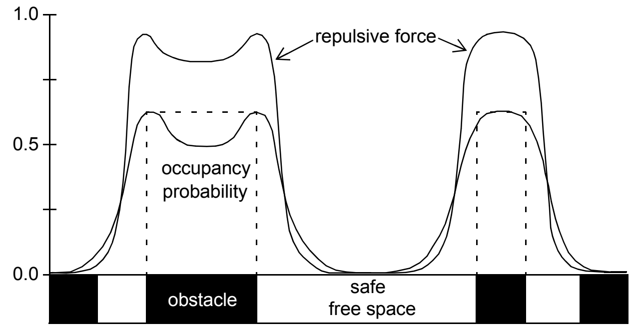

Fig. 3. Repulsive potential force computed directly from a probabilistic occupancy grid.

interior parts of obstacles are among those areas. Therefore, care must be taken that these parts of 3-D space be mapped to a strong repulsive potential field to prevent the path planner to consider the inside of obstacles and the unmapped space as free space. A suitable repulsive potential function must then produce a reinforcement of the repulsive field in regions where the occupancy probability is not clearly determined. Such a function to compute a repulsive force, F_{rep}, directly from the occupancy probability, *p[occ]*, associated with each voxel of the model has been developed to provide the desired behavior:

$$F_{rep} = \frac{1}{1 + e^{-10(p[occ] - 0.4)}} \tag{1}$$

This function reinforces the repulsive potential field in regions having an occupancy probability higher than 33%.

Considering again the set of two obstacles, both being measured by a sensor from their left and right sides respectively, the occupancy probability and the repulsive force distribution resulting from eq. (1) are shown in figure 3. In comparison with the repulsive force obtained from a discrete model of the same environment (figure 2), the center of large obstacles exerts a lower repulsive force than their boundaries. This is a normal consequence of the fact that the occupancy state of the interior of objects cannot be measured because of occlusions from the object surfaces. Nevertheless, the definition of the repulsive force distribution as a function of the occupancy probability ensures that the repulsive field associated with an unknown space (*p[occ] = 0.5*) is never less than 0.73 over a normalized maximum of 1.0.

Therefore, a path planner of any type can rely on this repulsive force to avoid collisions provided that it is programmed to prevent any component of the robot to traverse any area where the repulsive force is higher than 0.73. This critical value is arbitrarily chosen but can be justified by the fact that the reinforcement process of the occupancy probability that occurs during the modeling phase ensures that the first measurement taken on a regions that is occupied by an obstacle results in a minimum occupancy probability of 0.64. The corresponding repulsive force, following eq. (1), is then 0.92. This means that as soon as an obstacle is detected with at least one measurement from the sensor, a strong repulsive force will appear and repulse the robot from traversing the cluttered area.

Another advantage associated with the use of probabilistic occupancy models for the estimation of a repulsive potential field is that beyond the occupancy state, the probabilistic grid also encodes the available knowledge about the uncertainty on the objects position and orientation. This supplementary information is not available from discrete grids since the representation can only be binary (*occupied* or *empty*). Given the continuous encoding that makes the occupancy probability reach extreme values (close to 0.0 or 1.0) only where the confidence of the state of space is high, there is no need for a security margin to be added to virtually inflate obstacles when a probabilistic model is used.

The smooth variation of occupancy probability ensures that the repulsive force also varies smoothly from its maximum to its minimum value when one moves from cluttered to free areas. The rate of variation is automatically adjusted as a function of the level of uncertainty on the position and orientation of the obstacle surfaces. Therefore, the extent of the area covered by a highly repulsive force is set automatically as a function of the level of confidence in the model independently for each region. This reveals to be a critical advantage when models need to be refined progressively while the robot is moving around the scene.

The repulsive potential field is computed by a traversal of the probabilistic octree encoding the model of the environment. This process provides a new octree of a similar topology but with different values associated with each cell. These values are the repulsive forces for each region of space following the obstacles distribution. The use of such an octree to store repulsive force values preserves the compactness of the encoding scheme while facilitating the access to data.

Figure 4 presents the repulsive potential field computed from the model of figure 1. White voxels correspond to a

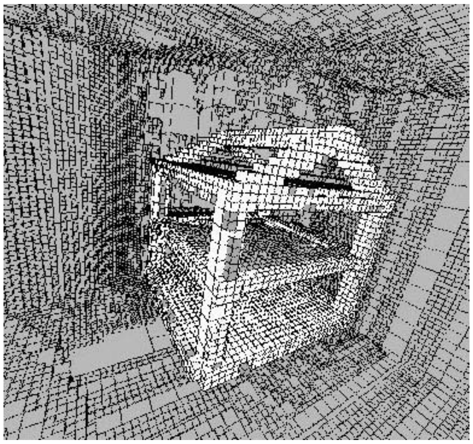

Fig. 4. Repulsive potential field associated with the 3-D probabilistic model shown in figure 1.

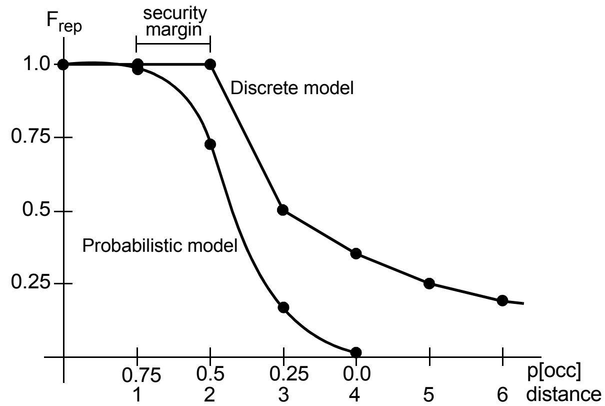

Fig. 5. Characteristic distribution of repulsive potential fields computed from discrete occupancy grids and from probabilistic models.

strong repulsive potential field located all around the components of the tubular structure. Gray areas located all around the scene represent an intermediate repulsive force (0.73) associated with regions that have not been scanned by the range sensor. This prevents the robot from circulating in unexplored spaces.

This example demonstrates that a suitable repulsive field can be obtained without computing any distance table when a probabilistic model is used, thus reducing computing time. For this example, the whole repulsive field is computed within 0.5 second for an entire cubic region of 1680 mm along each side encoded in an octree having 1024^3 cells.

Figure 5 shows the characteristic distribution of repulsive forces along the boundary of an object as a function of the distance with respect to this object. With both the discrete and the probabilistic modeling approaches, the repulsive potential field is strongly repellent nearby the obstacle boundary. However, the repulsive force computed from probabilistic models tends to decrease faster when the robot moves away from the objects. This behavior results from the elimination of the arbitrary security margin (here considered to be a single voxel wide) and from the definition of the repulsive force. This is another advantage of the use of probabilistic occupancy grids for path planning as an efficient path planner should prevent the robot from being significantly influenced by an obstacle that is located at a relatively large distance. This reveals to be a critical issue in maximizing possibilities to find a free and safe path.

B. Computing an Attractive Potential Field

The attractive potential field guides the mobile robot or the end effector of a manipulator toward its goal in Cartesian space. An interesting strategy to build attractive fields consists of defining a potential surface that contains no local minima except at the goal point to be reached by the robot. This allows the robot to follow the steepest gradient of potential while it moves from a given configuration to the goal without getting trapped away from the desired destination.

To build the discrete potential field, classical approaches define free space skeletons similar to Voronoï diagrams [13] that are computed by lengthy wave propagation techniques. A free space skeleton is defined as the area where waves emitted by all obstacles reach each other, that is the farthest locations from all objects. Following this free space skeleton ensures that the path followed by the robot stays away from the obstacles while guiding its displacement toward the goal.

To determine the attractive field, cells that are member of the free space skeleton are visited successively on the basis of their neighborhood. Starting from the desired destination for the robot, a progressively growing potential value is tagged to each cell until the totality of free space is covered. These tags are finally used by the path planner to find a free trajectory for the robot from the current configuration to the goal by following the negative gradient of the attractive field.

The approach that is introduced here makes use of probabilistic occupancy models to directly compute an attractive discrete potential field that is free of local minima. Instead of extracting a free space skeleton from a time consuming wave propagation, a simple traversal of the probabilistic occupancy model is performed and cells whose occupancy probability is lower than a given threshold (considered safe) are tagged as candidates areas for the robot to circulate.

This simple process results in a network of channels that are free and sufficiently far away from all obstacles in their vicinity. This network is encoded as a quadtree or an octree to facilitate further data processing. The resulting tree structure consists of a subset of the initial model which contains only those cells whose occupancy probability is lower than the threshold. Figure 6 illustrates the thresholding process applied on the occupancy probability in order to define free space channels. Depending on the nature of the task, the thresholding

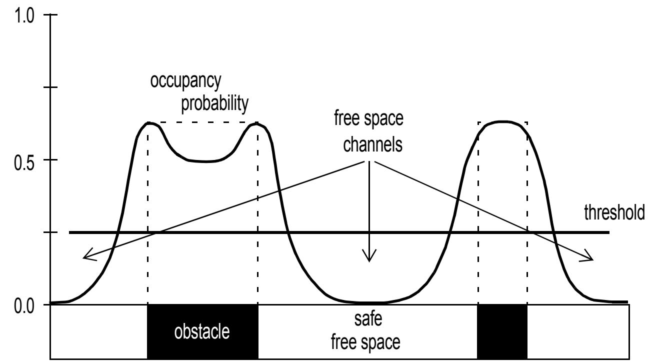

Fig. 6. Free space channels defined as regions having a low occupancy probability.

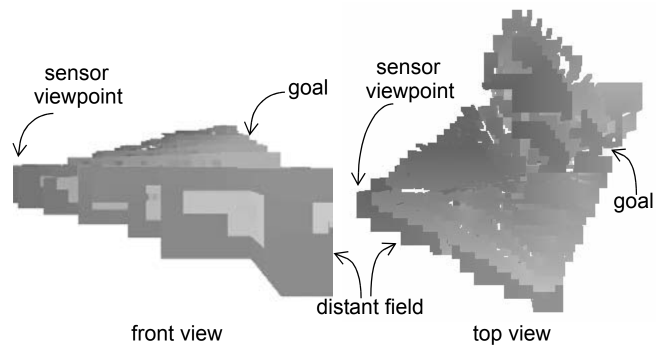

Fig. 7. Attractive potential field around the 3-D scene showing variations in attractive force proportional to distance from the goal.

value is set as a function of the admissible risk for the robot to come into collision with an obstacle.

Once the network of free space channels is defined, member cells are sequentially visited on the basis on their neighborhood, starting from the goal to be reached by the robot. Advantage is taken of an efficient neighbor finding algorithm that has been developed in this context to operate on quadtrees and octrees [14]. Consequently, an attractive potential field with a single minimum is built that precludes the robot from getting trapped away for the desired destination.

Figure 7 shows two views of the attractive field computed from the probabilistic model of the tubular structure of figure 1. Potential levels are mapped as grayscales. Light gray cells correspond to those being closer to the goal while darkest cells are located a larger distances from the goal. Visualizing such 3-D representations computed on complex scenes reveals to be difficult as the cells that are drawn are all located into a compact area forming the free space channels. Therefore, these cells are not part of the objects and can hardly be recognized. They are rather associated with empty regions in the 3-D structure. However, progressive variations in grayscale show that the labelling of the attractive field makes it converge toward the desired destination. Sensor viewpoints and scanned empty areas are also put in evidence.

Taking advantage of the continuous representation of the occupancy probability, no distance table is required to compute this local-minima free attractive potential field. After a threshold is applied by a traversal of the whole model, determination of the attractive field is straightforward and computationally efficient as the number of cells to visit is limited to those that correspond to real empty space. As a result, computing time can then be significantly improved over traditional approaches. In the present example, determination of the free space channels is achieved within 0.3 second while the estimation of the entire attractive field takes about 20 seconds for our model of 1024^3 cells when running on a Pentium III - 933 MHz.

IV. EXPERIMENTATION WITH PATH PLANNING

In order to evaluate the performances of the proposed path planning approach, tests have been conducted on various environments. Figure 8 presents an example of a 2-D map (for clarity) on which path planning has been performed when objects are mapped either with a discrete occupancy model or with a probabilistic model. Resulting paths computed from an attractive potential field obtained from the probabilistic model are compared with the paths that result from an attractive potential field computed from a discrete occupancy model.

It is interesting to note that resulting paths are not significantly influenced by the nature of the model used to compute potential fields. However, when the fields are obtained from a probabilistic model, advantage can be taken of supplementary information contained in the model to define extra criteria to drive the selection of the next best neighbor cell to visit along the path. For example, two different criteria have been privileged here: i) the neighbor cell with the minimum number of steps required to plan a full path; or ii) the neighbor cell with the minimum occupancy probability to keep the robot as far as possible from the obstacles and the boundaries of the model (beyond which the state of space is unknown) and improve the security level of the path.

Even though none of these paths can be considered optimal, operating on probabilistic models clearly provides supplementary flexibility to the path planner according to the hazard level associated with the task to perform. When path planning relies on discrete occupancy grids, only a neighbor selection based on distance is possible since no complete knowledge about the occupancy probability is available and all cells are either certainly empty or certainly occupied. There is no possibility then for the path planner to adjust the tolerance or the risk level to help in overcoming critical situations like narrow corridors between obstacles. The only solution reduces to a proper selection of the security margins, but this remains a challenging issue.

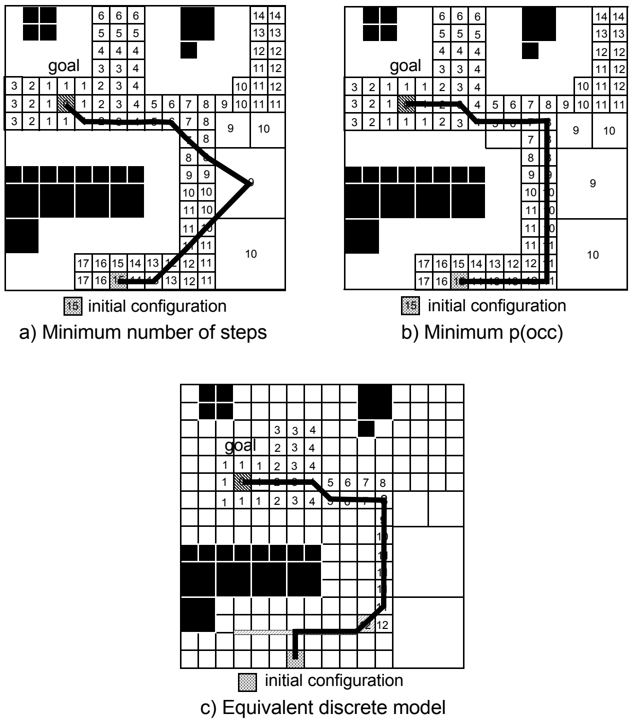

Fig. 8. Paths resulting from the use of various criteria on a probabilistic model compared with the path computed on an equivalent discrete occupancy model using classical approaches.

V. CONCLUSION

In this paper, a new approach has been introduced that takes advantage of probabilistic occupancy model characteristics to build repulsive and attractive potential fields in 2-D and 3-D environments. The continuous nature of the occupancy probability encoded in such models allows direct computation of the repulsive potential field without any intermediate distance table. Similarly, the domain of free space areas located far enough from obstacle boundaries is processed without a computationally intensive wave propagation and search for wave intersection.

Moreover, since a probabilistic occupancy model includes knowledge about the uncertainty on the obstacles position and orientation, there is no need to impose an arbitrary security margin around obstacles to ensure the robot's safety, as in most classical path planning methods using discrete occupancy grids. In the areas where an obstacle is not clearly defined, the occupancy probability is a direct measurement of this situation. If both potential fields are computed directly from the occupancy model, the fields automatically reflect these uncertainties and do not lead the robot through risky areas. Overall, enlargement of the free space is observed, leaving more space for the robot to circulate, especially in narrow areas. The path planning success rate is then increased.

Initial experimentation in 2-D space demonstrated that the computational workload can be reduced by about 30% when a probabilistic encoding scheme is used instead of classical occupancy representations [15]. Encoding the probabilistic model as a multiresolution structure allows an extra 40% reduction of the computation time in general. Attempts with the extension of this path planning strategy in 3-D space also confirmed these observations.

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