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Robot Navigation Algorithms Using Learned Spatial Graphs

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Engineering Physics and Mathematics Division

ROBOT NAVIGATION ALGORITHMS USING LEARNED SPATIAL GRAPHS*

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ABSTRACT

Finding optimal paths for robot navigation in known terrain has been studied for some time but, in many important situations, a robot would be required to navigate in completely new or partially explored terrain. We propose a method of robot navigation which requires no pre-learned model, makes maximal use of available information, records and synthesizes information from multiple journeys, and contains concepts of learning that allow for continuous transition from local to global path optimality. The model of the terrain consists of a spatial graph and a Voronoi diagram. Using acquired sensor data, polygonal boundaries containing perceived obstacles shrink to approximate the actual obstacles' surfaces, free space for transit is correspondingly enlarged, and additional nodes and edges are recorded based on path intersections and stop points. Navigation planning is gradually accelerated with experience since improved global map information minimizes the need for further sensor data acquisition. Our method currently assumes obstacle locations are unchanging, navigation can be successfully conducted using two-dimensional projections, and sensor information is precise.

Keywords and phrases: Learning, Spatial Graph Model, Robot Navigation, Local Optimization, Path Problems, Voronoi Diagram.

1. INTRODUCTION

Robotics has become an actively pursued research area of computer science and has proven to be replete with a variety of issues ranging from abstract mathematical to highly pragmatic problems. In many industrial applications which are repetitive and tedious (e.g., normal maintenance or inspection), it would be desirable to utilize mobile robots. Other tasks requiring rapid response in emergency situations are also appropriate for intelligent machines; this is particularly true in hazardous environments. Some of the more active robotics research areas today include knowledge representation, task planning, multi-sensor interpretation, dynamics and control, advanced computer architectures, algorithms for concurrent computation, and coordinated manipulation and navigation.

A robot may be characterized as an autonomous machine capable of decision making and action. To perform complex tasks which cannot be fully programmed *a priori*, effective sensing becomes crucial for monitoring both the robot's environment as well as the status of its own internal system. There have been several efforts to design an automated mobile robot. Examples are SHAKEY,[1,2] the JPL robot,[3] HILARE,[4,5] the Stanford Cart,[6] the CMU Terregator and Neptune robots,[7] Yamabico,[8] and HERMIES.[9]

Navigation planning is one of the vital aspects of any mobile robot. One approach toward navigation, called the find-path problem, addresses itself to determining a collision free path for a robot moving through a terrain cluttered with obstacles whose positions are known. This problem is well understood and solved in many cases.[10-18] The techniques for navigation described in these papers assume that a complete global model of our obstacle laden environment is known. Most of the techniques above model the obstacles and the free space of a robotic environment as mathematical and geometric entities. When a robot must navigate in an unexplored environment, the algorithms are not directly applicable.

Navigation in the more general case calls for the collision free movement of a mobile robot in entirely or partially unexplored terrain. The problem of planning optimal or near optimal paths that avoid collisions with obstacles in such an environment is a challenging task. Contrary to the known environment case, there has not been as much work reported in the literature about navigation problems in unexplored terrain. This can be attributed to the inherent ambiguity of the problem due to the lack of global information about the obstacles. Early attempts to navigate in unexplored terrain were based solely on image understanding.[3,6] More recently, Crowley[19] and Parodi[20] have suggested hierarchical approaches with global and local models updated based on sensor feedback. Chattergy[21] describes some novel heuristic strategies to aid the navigation of a robot in an unexplored terrain. This paper builds upon many of these ideas but specifically aims toward a method for which no pre-learned model is required, information from multiple journeys is explicitly synthesized, all information is used to the maximum extent, and a global path optimization is achieved in a continuous transition from local path optimization as more information is acquired.

In this paper, we assume that the robot (HERMIES)[9] begins his task in a completely unexplored terrain of finite dimensions. HERMIES has to complete a number of different traversals (e.g., carrying objects from place to place) and the goal of this paper is to provide the method by which he can navigate more efficiently with each successive trip, based upon experience acquired to date. The terrain can be randomly populated with obstacles, but the world is assumed to be static. The robot, assumed to be a point in a two-dimensional plane, can recognize line-of-sight distances to objects and detect their edges without imprecision.

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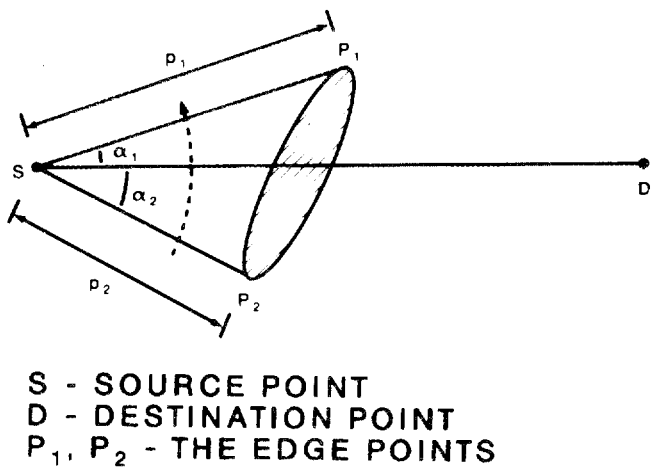

Fig. 1. The sensor readings include α_1, α_2, P_1 and P_2.

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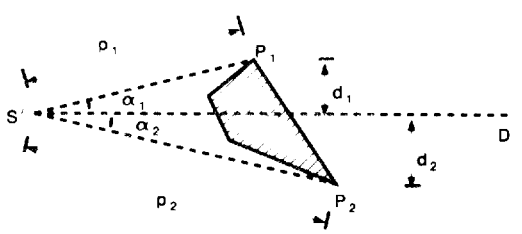
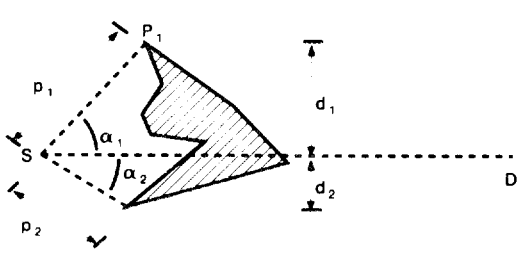


(a) CONVEX POLYGON



(b) NON-CONVEX POLYGON

OPTIMALITY CRITERION $\longrightarrow$ $\min(d_1, d_2)$

$\longrightarrow$ $\min(p_1 \sin\alpha_1, p_2 \sin\alpha_2)$

Fig. 2. First case for local optimization.

The terrain is modelled using an attribute graph, called a *spatial graph*, and a *Voronoi diagram*. Initially, both are empty, and they are updated as more and more paths are traversed. Each path of navigation is composed of a sequence of stop points, where the robot stops to take sensor readings, or to access the terrain model to compute the next stop point. The robot travels in straight lines in between two successive stop points. Initially, obstacle avoidance techniques use local optimization for the navigation of the robot. By local optimization we mean optimal path selection based only on sensor information at the time of the decision.

Traversal of paths includes sensor exploration of the regions in which the robot navigates. Information gained while on new paths is consolidated into the existing graph structures. In planning any path, the content of the current graphs is made use of to the maximum possible extent, and local optimization occurs in the regions where no model is available. Initially, since no graph is available, the paths are only locally optimal. As more and more paths are traversed, the graphs become more complete ('learned') and gradually improve from local optimality to global optimality.

2. OPTIMIZATION OF LOCAL OBJECT AVOIDANCE

When a robot navigates in new terrain with no *a priori* information, its path of navigation is completely decided by the sensor readings and presumed goal destination. The localized nature of the sensors makes a true globally optimal path determination impossible in a terrain with arbitrary distribution of obstacles. Thus, a local optimization scheme must be used to determine the path of navigation in the immediate proximity of obstacles.

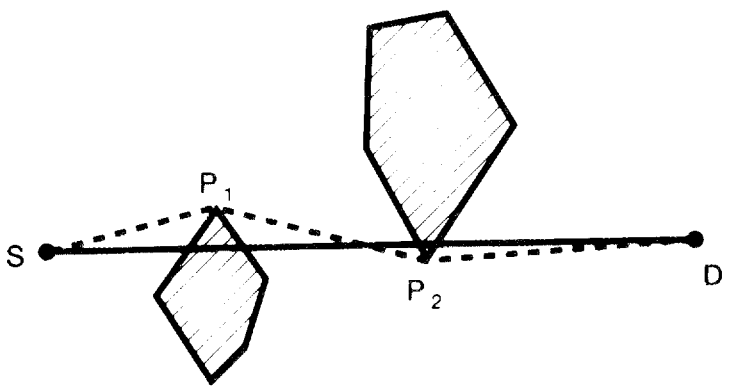
We consider the obstacle that is nearest to the source point S in the direction of the robot's goal destination. The sensor readings obtained allow for determination of the distance from the source to the edges of the obstacle, and also the corresponding edge angles relative to the line between the robot center and the goal. In Fig. 1, the angles α_1 and α_2 and the distances p_1 and p_2 are obtained from sensor readings. Our local optimization approach considers two cases. Figure 2 depicts the first case for which no part of the obstacle extends beyond the source point in the direction opposite to the direction of the next robot destination. The local optimization criterion is to minimize the distance traversed in the direction perpendicular to the line joining the source point S to the destination point D. That is, the locally optimal path is given by the condition min (d_1,d_2) or min $(p_1 \sin \alpha_1, p_2 \sin \alpha_2)$. This method may not yield a globally optimal path as shown in Fig. 3. The path SP_1P_2D will be followed according to the local optimality criterion, but the path SP_3D will be globally optimal. The second case of local optimality involves the obstacles that extend beyond the source in the direction opposite to the direction of the destination point as shown in Fig. 4. In this case the distance traversed (f_1,f_2) in the direction opposite to that of destination point D also has to be minimized. Referring to Fig. 4, the criterion for local optimization is given by min $(\sqrt{d_1^2 + f_1^2}, \sqrt{d_2^2 + f_2^2})$. Again, it is to be noted that this method may not give rise to globally optimal solution.

3. TERRAIN MODEL

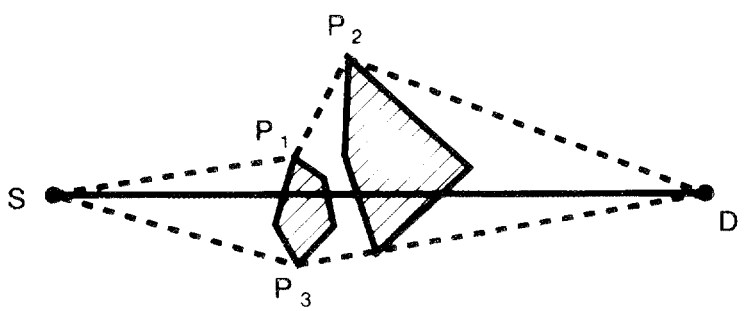
Figure 5 shows an illustrative rectangular terrain populated with four obstacles. Four paths are traversed using local optimization. The paths start at S_1, S_2, S_3, and S_4 and end at D_1, D_2, D_3, and D_4, respectively. The terrain in which the robot navigates is represented by both a *spatial graph* and a *Voronoi diagram* (Figs. 6 and 7, respectively).

LOCAL OPTIMIZATION ALGORITHM

```
ALGORITHM NAVIGATE-LOCAL (S, D);
   S THE SOURCE POINT.  D IS THE DESTINATION POINT
BEGIN
1.   IF D IS DIRECTLY REACHABLE
2.   THEN GO STRAIGHT
3.   ELSE
     BEGIN
4.     SCAN THE TERRAIN AROUND THE DIRECTION OF SD̄;
5.     P* ← OPTIMUM (P1, P2);
6.     GO STRAIGHT TO P*
7.     IF P* ≠ D
8.     THEN  NAVIGATE-LOCAL (P*, D);
     END;
END;
```



(a) BOTH LOCALLY AND GLOBALLY OPTIMAL



(b) ONLY LOCALLY OPTIMAL

Fig. 3. Local optimality does not mean global optimality.

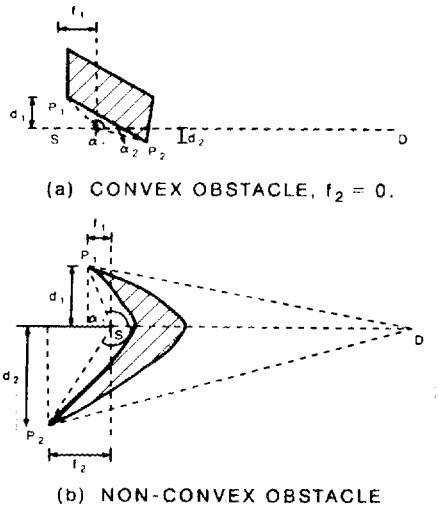
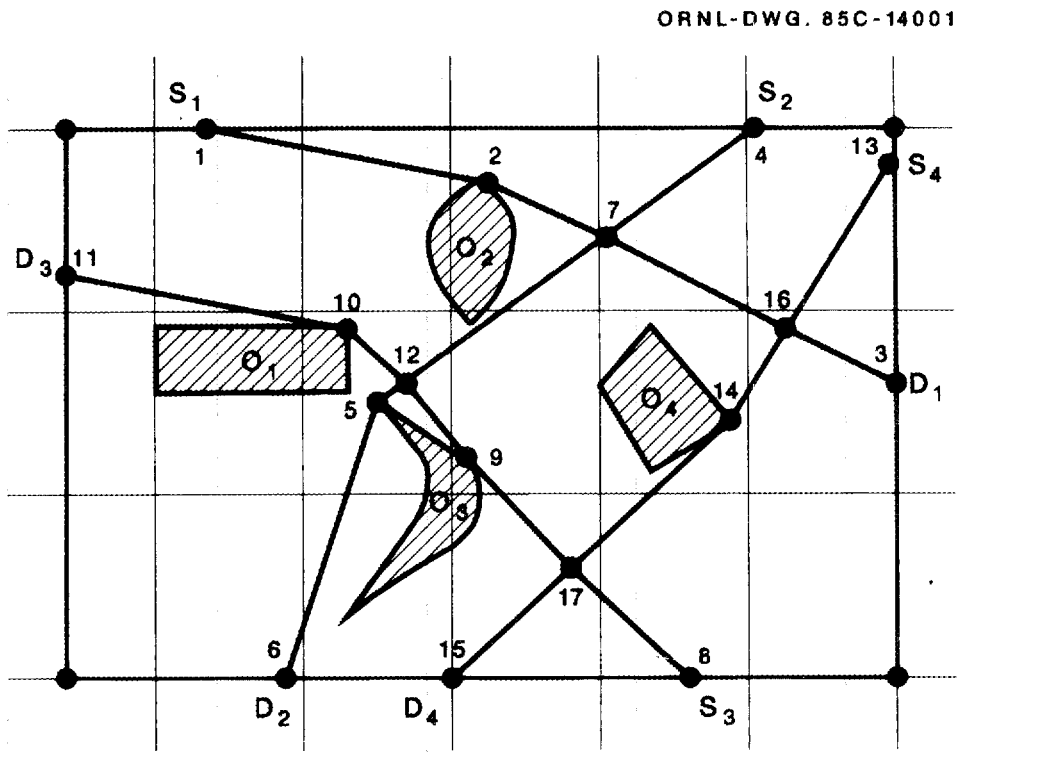


Fig. 4. Second case for local optimization.



FOUR PATHS FROM S_1, S_2, S_3 AND S_4 TO D_1, D_2, D_3 AND D_4 RESPECTIVELY USING LOCAL OPTIMIZATION. ALL PATHS ARE CONSOLIDATED BY FINDING INTERSECTION POINTS SUCH AS 7, 16, 12, AND 17

Fig. 5. The terrain.

A *spatial graph* G is defined as the ordered triple (V,E,ψ), where V is the set of nodes, E is the set of edges, and ψ is an *attribute mapping* that defines a pair of attributes (e.g., coordinate locations) for each vertex. For an edge $e = (v_i,v_j) \subset E$, we say that v_i and v_j are *connected* to each other. We also have a *distance* d(e) defined for each edge $e = (v_i,v_j) \subset E$, $\psi(v_i) = (i_1,i_2)$, $\psi(v_j) = (j_1,j_2)$, as

$$d(e) = \left[(i_1 - j_1)^2 + (i_2 - j_2)^2 \right]^{1/2} . \tag{1}$$

Initially a uniform grid is superimposed on the terrain of navigation. The granularity or grid size is chosen to be smaller than the expected size of the smallest obstacle of interest. The grid cells are numbered in the usual manner using x and y coordinate systems. Any path of navigation on the grid consists of straight lines and stop points. Each stop point corresponds to a node of the spatial graph, and each path joining two adjacent stop points corresponds to an edge. The pair of attributes of a node corresponds to the coordinates of the cell in which the node lies. The distance of an edge, $e = (v_i,v_j) \subset E$, is the euclidian distance between the nodes v_i and v_j. Figure 6 illustrates the spatial graph corresponding to the terrain and local optimization path planning of Fig. 5.

We next obtain a *Voronoi diagram* for the set of vertices, V, of the spatial graph given a set S of n points of $\{p_1,p_2,...,p_n\}$. The *Voronoi diagram* of S, Vor(S), partitions the plane into n equivalence classes, each of which corresponds to a point. Specifically, the equivalence class corresponding to point p_i is the *Voronoi polygon* $VP(p_i)$, defined[22] such that any point x in $VP(p_i)$ is closer to p_i than to any other point in S. Figure 7 illustrates the *Voronoi diagram* corresponding to the spatial graph of Fig. 6.

Initially, when HERMIES is first placed in a new terrain, the spatial graph is empty or null and the Voronoi diagram contains no points. The new paths are integrated into the terrain models when they are traversed. The spatial graph is updated for every new path as follows: (i) create new nodes corresponding to new stop points, (ii) create new edges corresponding to the paths in between two adjacent stop points, (iii) create new intersection nodes corresponding to the intersection points of new edges with the existing edges. When this process is complete, the Voronoi diagram is updated accordingly.

4. PATH PLANNING AND LEARNING

In this section we develop an algorithm that plans safe paths to navigate from a new arbitrary source point to a new arbitrary destination point. At each stop point on the path, either sensor readings are taken or graph computation is performed based on the existing terrain models to compute the next stop point. The terrain model is appropriately updated at each stop point.

Consider the navigation of the robot from the source point S to the destination point D. We compute *virtual source* S′ and *virtual destination* point D′, such that $S \epsilon VP(S')$ and $D \epsilon VP(D')$. In other words, S′ and D′ are the nodes of the spatial graph that are nearest to S and D, respectively. The paths from S to S′ and D′ to D are traversed according to the local optimization described in Section 2. The path S′D′ is planned using the spatial graph model and sensor readings, as will be described below.

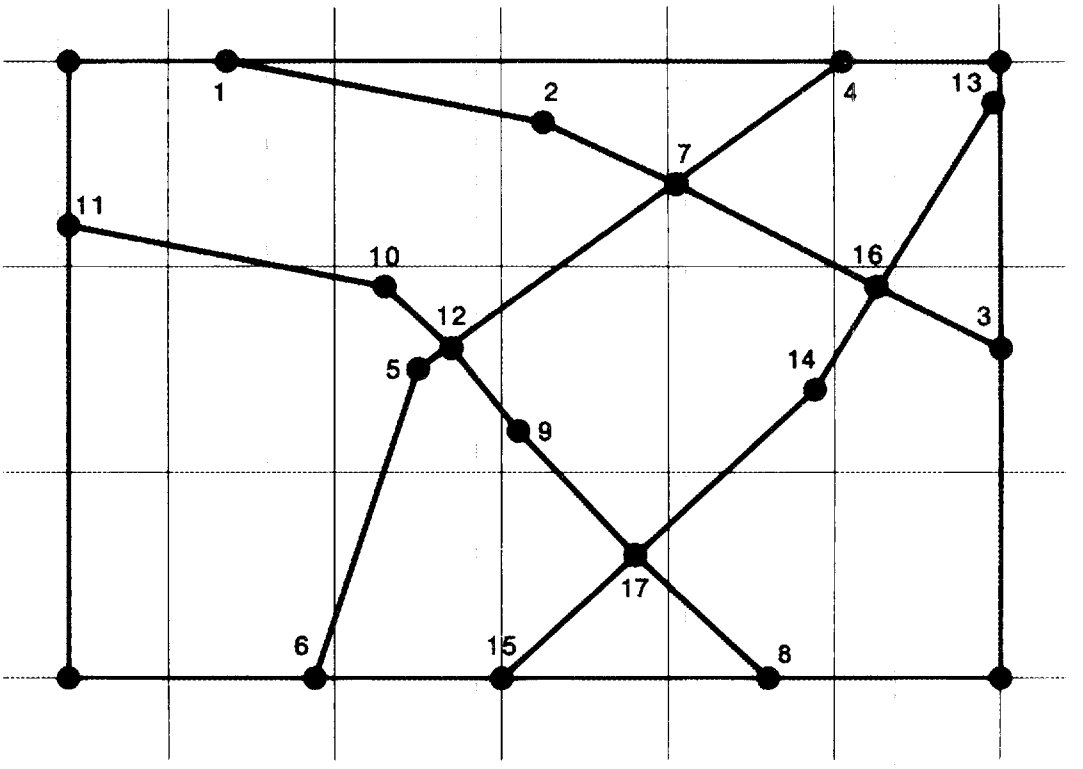


Fig. 6. The spatial graph.

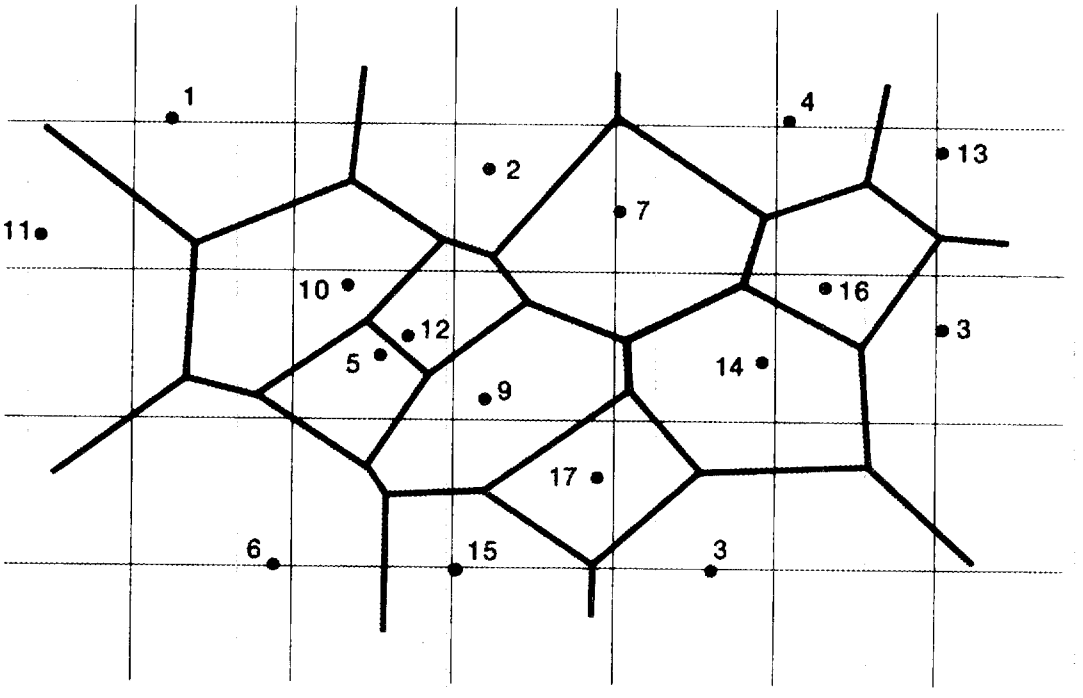


Fig. 7. The Voronoi diagram.

The paths from S to S′ and D′ to D can be navigated directly or constructed using the minimal distance to the spatial graph and following the graph to reach S′ (and D′) from the intersection point. The latter approach involves the creation of new nodes for the stop points and the appropriate edges. Also, the *Voronoi diagram* should be updated by creating new Voronoi regions for the new nodes. But the process of finding the virtual points should be carried out only after the graph is reasonably complete. That is to say, initially, until a considerable number of nodes are inserted into the spatial graph, all the navigation should be determined using sensor based algorithms. The basic algorithm is as follows:

COMPLETE NAVIGATION ALGORITHM

ALGORITHM NAVIGATE (S,D);
S IS THE SOURCE POINT, D IS THE DESTINATION POINT.
BEGIN
1. FIND S′ AND D′ SUCH THAT SϵVP(S′),
   AND DϵVP(D′);
2. NAVIGATE-LOCAL (S,S′);
3. NAVIGATE-GLOBAL (S′,D′);
4. NAVIGATE-LOCAL (D′,D);
   END.

The algorithm **NAVIGATE** (S′,D′) plans the path S′D′. This algorithm tests the polygon P, in which the source end of S′D′ lies. A polygon is said to be an *obstacle polygon* with respect to S′ if the obstacle or obstacles contained in P entirely fill the sensor range from S′, as shown in Fig. 8.

A polygon is a free polygon if it does not contain any obstacles. If the polygon P is unexplored with respect to S′, then the algorithm **EXPLORE (P,S′)** is involved. Sensor readings from S′ distinguish two types of regions — visible and invisible — as shown in Fig. 9. The *invisible* regions are the regions of the polygon that are not reachable by the sensor when the obstacles contained in the region are absent. The regions that are not invisible are called the *visible regions*. Based on the sensor readings, the polygon P can be partitioned into regions as shown in Fig. 10.

A region could be an unexplored polygon, a free-polygon, or an obstacle-polygon. The invisible regions are declared as unexplored with respect to the vertices on the line that limits the range of sensor from S′. The visible region is partitioned into obstacle polygons and free polygons. In Fig. 10 the region R_1 is unexplored with respect to the vertices P_1 and P_2. The regions R_2 and R_4 are free polygons, and the region R_3 is an obstacle polygon with respect to S′. It is to be noted that, in general, a polygon can be an obstacle polygon with respect to the other vertices. But, a polygon is a free polygon with respect to all the vertices of the polygon.

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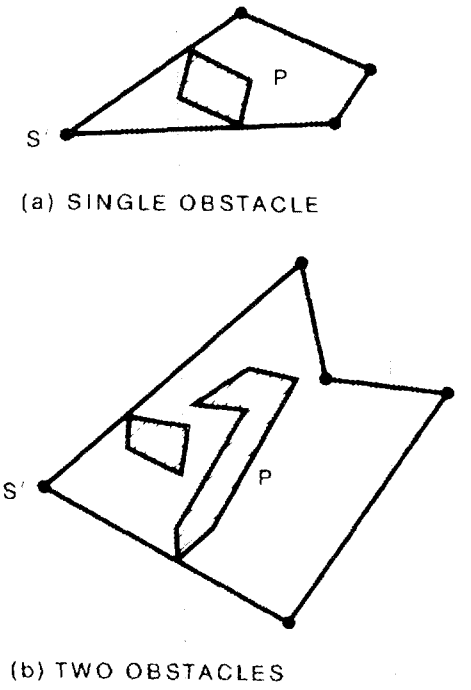

Fig. 8. Polygon P is an obstacle Polygon with respect to S′.

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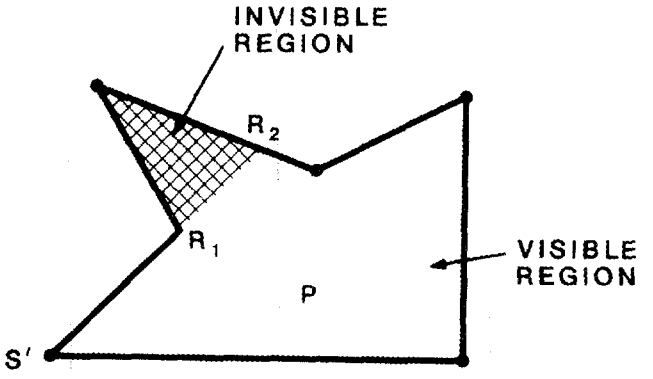


VISIBLE REGION: THE REGION REACHABLE BY A SWEEPING SENSOR, WHEN ALL OBSTACLES ARE REMOVED

INVISIBLE REGION: THE REGION NOT REACHABLE BY SWEEPING SENSOR, WHEN ALL OBSTACLES ARE REMOVED

Fig. 9. Visible and invisible regions with respect to S′.

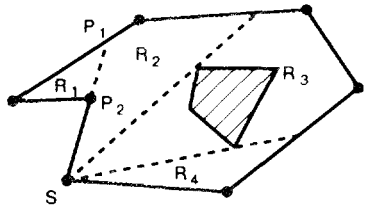


Fig. 10. Partitioning a Polygon based on sensor readings.

The algorithm **CONSOLIDATE** checks for any adjacent free regions from a convex region. If they form a convex region then it combines them and forms a single free polygon. The consolidation algorithm is described as follows:

CONSOLIDATION ALGORITHM

```
ALGORITHM CONSOLIDATE (P, S);
  P IS AN EXPLORED POLYGON WITH RESPECT TO VERTEX S
BEGIN
1.  FOR EACH FREE POLYGON P1, BELONGING TO THE
    PARTITION OF P        DO
    BEGIN
2.    FIND ALL ADJACENT FREE POLYGONS OF P1;
3.    FIND THE MAXIMAL SUBSET OF THEM THAT FORMS A
      CONVEX POLYGON AND COMBINE THEM INTO A SINGLE
      POLYGON;
    END;
  END;
```

The complete navigation algorithm for S′D′ is described in the Pascal-like syntax. The overall effect of this navigation algorithm is summarized as follows:

1. In general, all free polygons are convex and these polygon increase in size as learning proceeds.

2. Initially, all the obstacles are bounded by larger polygons, and as learning proceeds the bounding polygons are reduced in size to enclose the obstacles more closely.

3. If the path of navigation runs through all free polygons, then the complete path from S′ to D′ can be directly computed.

4. If the path contains unexplored polygons, then the robot halts at the appropriate stop point to explore the regions, and then the next stop point is computed only after the information about the currently explored region is incorporated into the terrain model.

5. Learning is incorporated along with path planning.

6. The paths are locally optimal initially, and they gradually become globally optimal as learning proceeds.

```
ALGORITHM NAVIGATE-GLOBAL (S', D');
  S' AND D' ARE THE SOURCE AND DESTINATION POINTS, RESPECTIVELY,
  ON THE SPATIAL GRAPH
  S'D' STANDS FOR THE STRAIGHT LINE JOINING S' AND D'
BEGIN
  FIND THE POLYGON P THAT CONTAINS SOURCE END OF S'D';
  IF (P IS AN OBSTACLE POLYGON)
  THEN
  BEGIN
    FIND THE NEAREST INTERSECTION POINT s OF S'D' AND P;
    FIND S*, SUCH THAT s ∈ VP(S*);
    MOVE TO S* ALONG EDGES OF P;
    NAVIGATE-GLOBAL (S*, D');
  END
  ELSE IF (P IS A FREE POLYGON)
  THEN
  BEGIN
    FIND THE INTERSECTION POINT s OF S'D' AND P;
    GO DIRECTLY TO s;
    NAVIGATE-GLOBAL (s, D');
  END
  ELSE IF (P IS UNEXPLORED WITH RESPECT TO S')
  THEN
  BEGIN
    EXPLORE (P, S');
    CONSOLIDATE (P, S');
    NAVIGATE (S', D');
  END;
END;
```

In the above algorithm we assumed the robot to be a point. However, the same can be applied to any finite sized robot by allowing suitable leeway in computing α_1, α_2, P_1 and P_2 from the sensor readings as shown in Fig. 11. However, a more generalized problem would be to consider the exact shape of the robot and plan the motion that involves both translation and rotation. Other natural extensions of the problem include the use of more than one sensor, and also taking into account the errors in distance measurement.

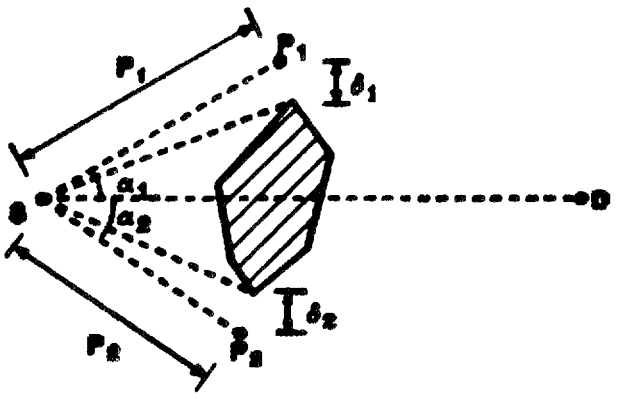


Fig. 11. Modification for a finite-sized robot: δ_1 and δ_2 account for the finite robot dimensions.

5. ILLUSTRATIVE EXAMPLE

In this section we illustrate our technique by tracing the algorithm of the previous section using a sample terrain. Figure 12 shows an unexplored terrain that contains four obstacles O_1, O_2, O_3, and O_4. Initially, four paths are traversed using local optimization from the source points S_1, S_2, S_3, and S_4 to D_1, D_2, D_3 and D_4, respectively. These paths are shown in Fig. 5, and the corresponding spatial graph and Voronoi diagram are shown in Fig. 6 and Fig. 7, respectively. Now consider applying the method of this paper to determining a path from S_5 to D_5. First, the virtual-source S' and virtual-destination D', are found as the nearest graph vertices corresponding to S_5 and D_5, respectively, as in Fig. 13.

The path from S_5 to S'_5 is traversed according to the local optimization method. The polygon P_2 contains the source end of the line $S'_5D'_5$. The polygon P_2 is unexplored and hence algorithm EXPLORE (P_2, S'_5) is invoked. The region P_2 is scanned using the sensor, and the polygon P_2 is partitioned into the regions P_2^1, P_2^2 and P_2^3 as in Fig. 14.

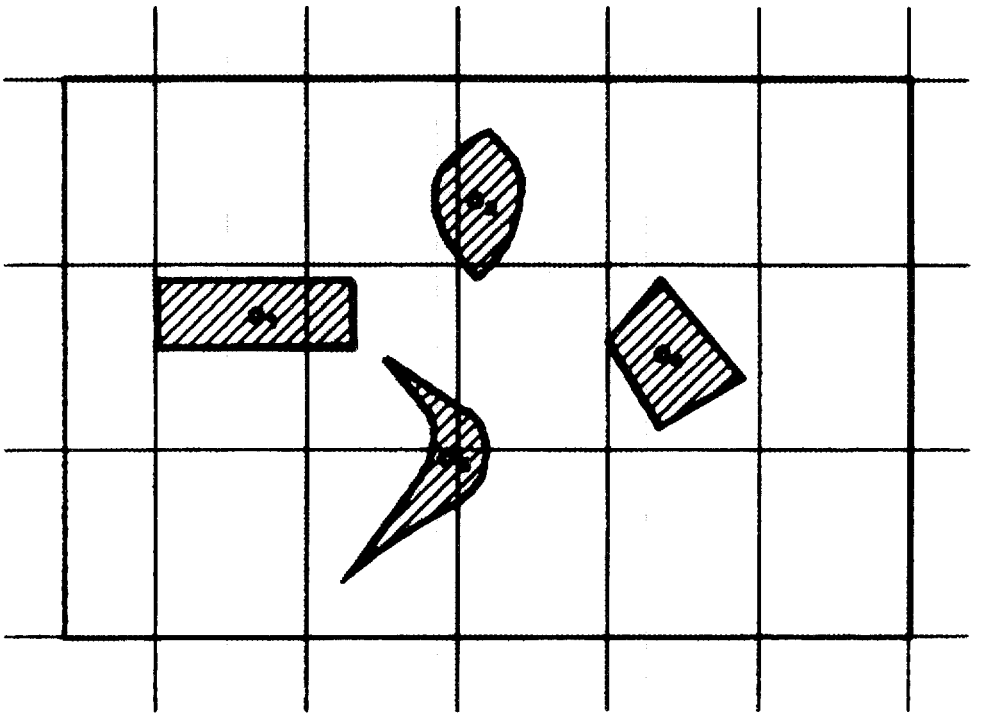
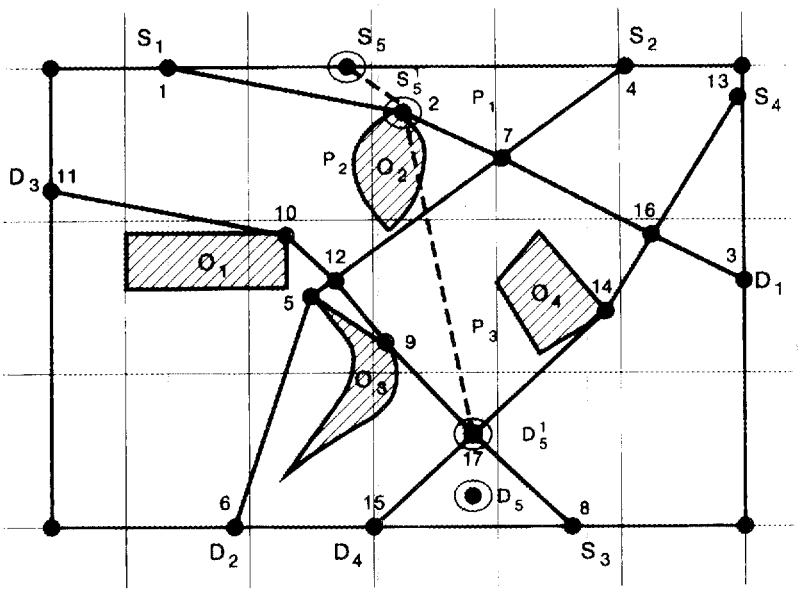
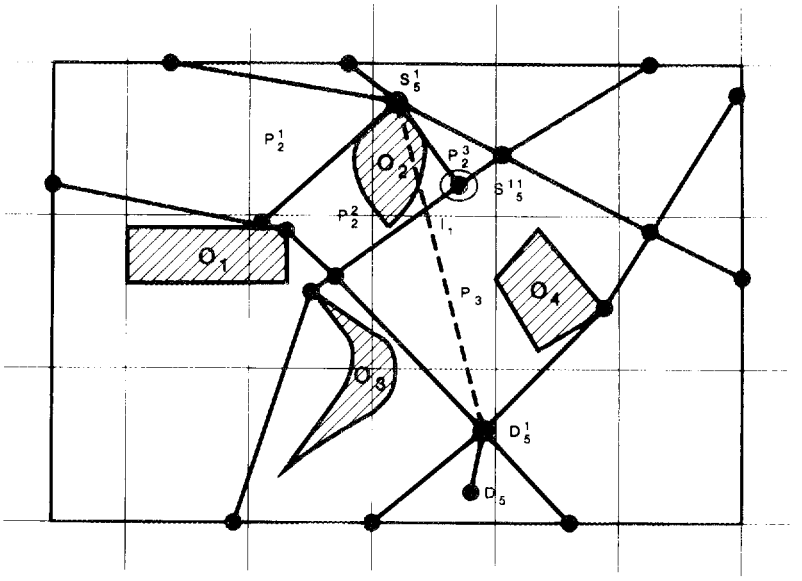


Fig. 12. Unexplored terrain.



CONSIDER NAVIGATION FROM S_5 TO D_5
S_5^1 IS THE VIRTUAL SOURCE $S_5 \varepsilon$ VPC (S_5^1)
D_5^1 IS THE VIRTUAL DESTINATION $D_5 \varepsilon$ VPC (D_5^1)
PATH FROM S_5 TO S_5^1 IS ACCORDING TO LOCAL OPTIMIZATION

Fig. 13. S_5 source point, D_5 destination point.



SOURCE END OF S_5^1 D_5^1 LIES IN POLYGON P_2
POLYGON P_2 IS EXPLORED
P_2 IS PARTITIONED INTO POLYGONS P_2^1, P_2^2, P_2^3
P_2^1, P_2^3 - FREE POLYGONS
P_2^2 - IS AN OBSTACLE POLYGON WITH RESPECT TO S_5^1
THE POLYGON P_2^2 IS PROCESSED, SINCE SOURCE END OF S_5^1 D_5^1 LIES IN P_2^2
THE INTERSECTION POINT I_1 IS COMPUTED, AND S_5^{11} IS
FOUND, SUCH THAT $I_1 \varepsilon$ VPC(S_5^{11})
PATH S_5^1 TO S_5^{11} IS TRAVERSED ALONG THE MINIMAL LENGTH
PATH ALONG THE EDGES OF P_2^2

Fig. 14. Exploration of Polygon P_2.

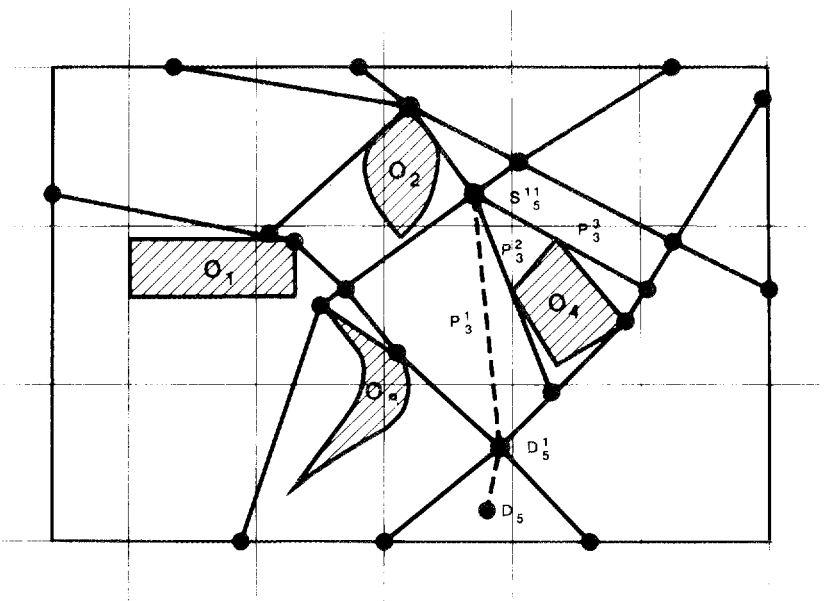


Fig. 15. Exploration of Polygon P_3.

The regions P_2^1 and P_2^3 are free-polygons, and the region P_2^2 is an obstacle-polygon with respect to the vertex S'. At this point, the source end of $S'_5D'_5$ is contained in the polygon P_2^2. The intersection point I_1 of $S'_5D'_5$ with the farther edge of P_2^2 is computed, and its nearest vertex S''_5 of the spatial graph is found. Then, the nearest path to S''_5 via the edges of the polygon P_2^2 is computed by finding the corresponding euclidian distance. The robot navigates along the edges of the polygon P_2^2 to reach S''_5. Next the path is planned from $S''_5D'_5$. The polygon P_3 contains the source end of $S''_5D'_5$ and is unexplored. Based on sensor readings, the polygon P_3 is partitioned into the regions P_3^1, P_3^2 and P_3^3. P_3^1 and P_3^3 are free polygons and P_3^2 is an obstacle polygon. At this stage, P_3^1 contains the source end of $S''_5D'_5$. The intersection point of $S''_5D'_5$ with P_3^1 is D'_5. The path of $S''_5D'_5$ is directly traversed as in Fig. 15. No update of the model is carried out since $S''_5D'_5$ is entirely contained in a free polygon. The navigation from D'_5D_5 is based on local optimization. The final spatial graph of the terrain is given in Fig. 16. Note that the obstacles O_2 and O_4 are bounded by smaller polygons than those shown in Fig. 5. Also, the polygons P_2^1, P_2^3, P_3^1 and P_3^3 are declared to be free polygons. Regions P_2^3 and P_3^3 are combined to form a single free polygon. Clearly, the information about the obstacles and free space of Fig. 16 is more consolidated and available for utilization than that of Fig. 5. Consider another navigation path from S_6 to D_6. The result of this traversal is shown in Fig. 17. Now the regions P_4, P_6 and P_9 are declared to be free polygons. The objects O_3 and O_4 are bounded by much smaller polygons than the ones in Fig. 16. Thus, the example illustrates the shrinking of the bounding polygons of the obstacles and widening of the free polygons as learning proceeds. Again, as more paths are traversed, more and more polygons are explored and the spatial graph becomes consolidated.

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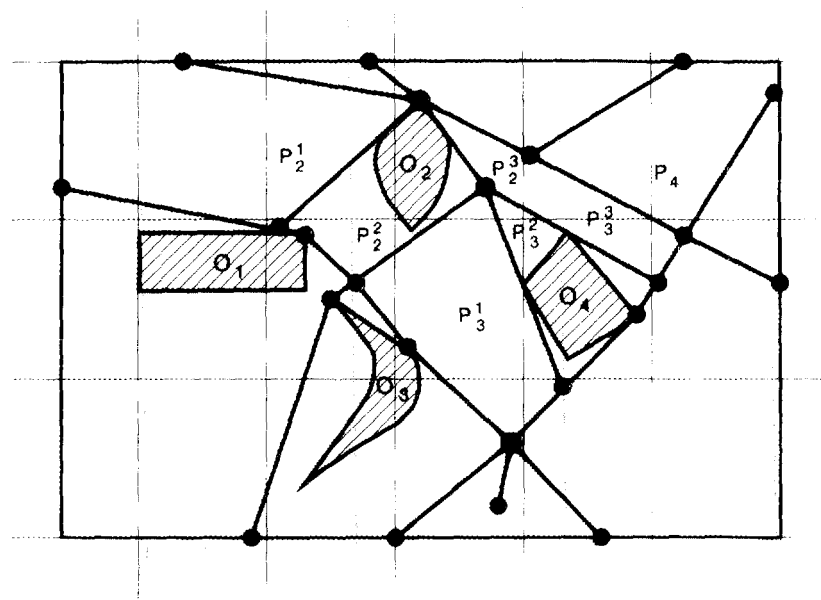

Fig. 16. Terrain model after the path from S_5 to D_5 is consolidated.

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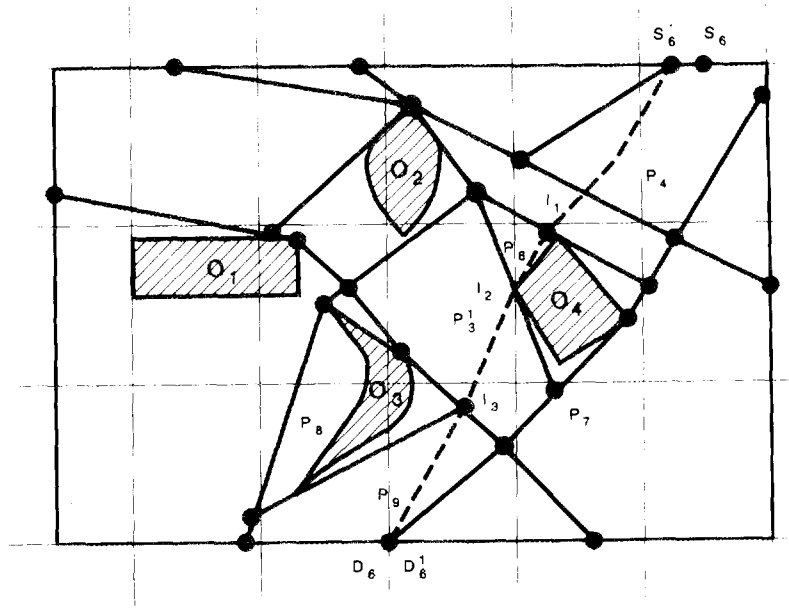

TRAVERSAL OF YET ANOTHER PATH FROM S_6 TO D_6

1. THE OBSTACLES O_4 AND O_3 ARE BOUNDED BY SMALLER POLYGONS
2. POLYGONS P_4, P_6, P_9 ARE DECLARED FREE POLYGONS
3. POLYGONS P_7 AND P_8 ARE DECLARED OBSTACLE POLYGONS WITH RESPECT TO I_1 AND I_3 RESPECTIVELY
4. PATH IS GLOBALLY OPTIMAL FROM S_6^1 TO D_6^1

Fig. 17. Terrain model after the path from S_6 to D_6 is consolidated.

6. CONCLUSIONS

In this paper, we describe a method that enables a mobile robot to navigate in an unexplored terrain and learn more about the terrain as it navigates paths. Our method requires no pre-learned model, makes maximal use of available information, records and synthesizes information from multiple journeys, and contains concepts of learning that allow for continuous transition from local to global optimality. The model of the terrain consists of a spatial graph and a Voronoi diagram. As more information is consolidated into the terrain model, the bounding polygons of the obstacles fit more closely and the polygons representing free space grow larger. In this way, the robot learns and applies the results of dynamically acquired sensor information to improve performance and relax navigational ambiguity on a continual basis up to the point where the environment is fully described; i.e., all obstacle-polygons are tightly bounded.

This paper has introduced the concept of learning in the domain of robot navigation and movement, namely path traversal and planning through a two-dimensional Cartesian environment. The utilization of concepts of spatial graphs has much broader implications however. For example, the rates at which sensor data updates are applied to the spatial graph directly affect the potential of the robot to navigate in a changing environment. Voronoi regions under a learning navigation paradigm can expand or shrink as a result of changing environmental conditions. The present spatial graph reflects only decisions arrived at from analysis of sensor data, but the method also permits the fusion of multiple sensor sources such as simultaneous use of line-of-sight (visual) and sonar to compose a simple graph space.

Similarly, there is no reason to confine the dimensionality of the graph to an N of two. For example, by extending the two-dimensional polygons to three-dimensional volumes, traversal in three dimensions and the learning of three-dimensional spaces become possible. A typical extension could be three-dimensional path planning of a robot end effector during grasping behavior scenarios. Further, the spatial graph nodes do not have to represent a single value. They can, for example, be pointers to complex data structures which contain a variety of relational data about a robot environment. In this way during path planning a spatial graph can serve as a context sensitive procedure for data base search by limiting the potential set of world data to local Voronoi regions and their associated data sets. In this manner, decisionmaking can be aided through "context focusing" which makes use of the spatial localization of the robot. Details of data structure and complexity analysis of the proposed algorithms are covered in a different paper.

7. FUTURE DIRECTIONS

Research is currently underway to extend the completeness of learning concepts to HERMIES navigation. In reality, true learning involves the utilization of more extensive sets of information such as those contained in complex data structures. Typical data include time tags, inter-object relations, tentative object classifications or labels. At present, we are extending learning to demonstrate performance on the HERMIES-II robot at CESAR by incorporating consolidation, abstraction, and forgetting processes. The latter deserves some comment. Forgetting or selective removal of information becomes more important for dynamic navigation if environments change to prevent the accumulation of useless data such as graph locations of moving objects in the environment. We propose to explicitly consider "forgetting" of spatial graph information by attaching a reinforcement or extinguishing time-based value to polygons. Values are decremented (i.e, extinguished by a fixed amount) unless a polygon is reinforced (confirmed) by additional sensor contacts. Such additions represent a more complete implementation of learning mechanisms traditionally associated with human psychological research.

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