T^*: A Novel *Terrain*-Based Path Planning Method for Mobile Robots

Ayanna Howard*, Homayoun Seraji, Barry Werger
NASA-Jet Propulsion Laboratory
California Institute of Technology
Pasadena, CA 91109, USA
*howard@helios.jpl.nasa.gov

Abstract

This paper presents a novel global path planning method for field mobile robots operating on rough natural terrain. The focus of this approach is on *terrain-based* path planning in which an optimally safe path of minimum traversal cost is constructed given the traversability characteristics of the terrain. The novelty of this method is the incorporation of the *Traversability Map*, a multi-valued map representation of traversal difficulty of terrain segments, into the path planning logic. The search methodology uses a traversal cost function that is defined by the user and is derived directly from this Traversability Map. The path planning method is developed in detail and both computer simulation and field test results are presented.

1. Introduction

With sensor-based local navigation strategies, an autonomous mobile robot operates in an unknown environment using locally-sensed information. This allows actions to be performed without the need to build an exact world model or to use complex planning processes. Although such strategies allow the robot to operate in real-time by requiring minimal memory storage and computational resources, the robot is not guaranteed to select the best path to its goal, or even attain its goal. Situations can arise in which the robot becomes trapped locally during exploration, unable to reach its desired goal location. This realistic possibility is detrimental to the mission, resulting in lost time and resources that can ultimately lead to mission failure. However, the performance of such locally-based navigation strategies can be improved significantly when prior global information is available. By utilizing a global path planner to specify a path between the start and desired goal locations, goal attainment can be evaluated before actual traversal, and thus the probability of mission success will be enhanced significantly.

The process of planning global paths for robots operating on harsh, natural terrain is a difficult task. Traditional path planners use the concept of goal-attainment, while avoiding obstacles, as the driving force. In order to allow successful completion of robotic exploratory missions in high-risk access terrains, we have developed a novel *terrain-based* global path planner that focuses on developing a path of minimum traversal cost while incorporating terrain characteristics. The method focuses on creating a traversability map based on global terrain features and plans paths accordingly. The traversability map has a multi-valued representation and denotes the ease-of-traversal of different regions of the terrain. By segmenting the global terrain into regions with distinct traversability characteristics, map modeling can cover a larger ground area than an obstacle-based representation, while still maintaining the same computational load. For path designation, the planner calculates a series of waypoints passing through regions of this traversability map. These waypoints are later integrated with regional terrain assessment navigation logic, as well as with local hazard avoidance behavior, to develop a complete navigation scheme capable of traversing long distances (Figure 1).

The main difference between this focus and traditional global planning methods is that both navigational safety and traversal cost are analyzed using aerial imagery or land surveying data. The motivations for this approach are to: 1) reduce the computational resources necessary for terrain-based path planning by incorporating a *minimalist* representation of the terrain using the Traversability Map, and 2) develop a *safe* path

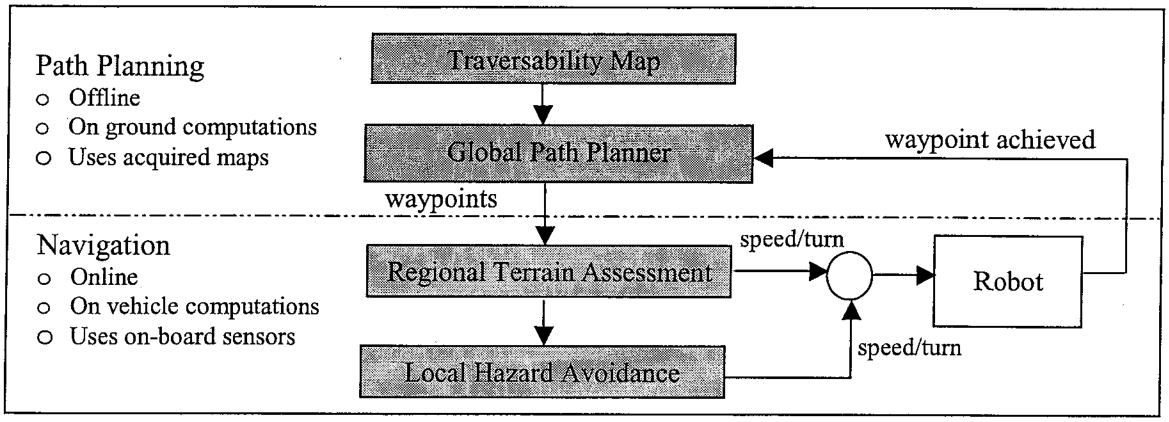


Figure 1. Terrain-based robot navigation scheme

which connects start and goal locations with regard to terrain features.

2. Background

Traditional path planning methods [see, e.g., 1] focus on a binary representation of the terrain from an obstacle occupancy point of view. Specifically, the terrain is segmented using a grid representation and binary values (0 or 1) are assigned to the cells in the grid. In this case, traversable obstacle-free cells are represented by 0, and 1 denotes an untraversable cell occupied by an obstacle. A more comprehensive approach to terrain representation is to characterize the presence of an obstacle in a grid cell using non-binary values. In this setting, a grid cell is not assigned a binary value, but instead is given a continuous value that represents the probability distribution for occupancy of the grid cell by an obstacle [2]. Even these comprehensive representations only account for the obstacle presence and disregard the intrinsic terrain properties. As such, they facilitate obstacle-based path planning but do not address terrain-based path planning. Once an *obstacle-based* grid representation is constructed, traditional path planners generate the shortest path that connects the robot's start and designated goal positions while ensuring untraversable cells are circumvented. In these approaches, there is no provision for representing ranges of impassability. In addition, if the constructed surface map encompasses a large area, the planning process becomes computationally intense and the large memory required for map storage makes the method incapable of replanning in a time-efficient manner. There has been some efforts in developing regional planners that overcome these limitations [3,4], but they still utilize a binary obstacle-based representation for map construction. These efforts (RoverBug and D*) fall under the category of sensor-based motion planning in which the robot uses a simple representation of obstacles detected with on-board sensors, to conserve both memory and computational resources, and to avoid obstacles while traversing through rough terrain. These algorithms construct local path segments based on the sensed environment and use this information to re-plan paths in an incremental fashion.

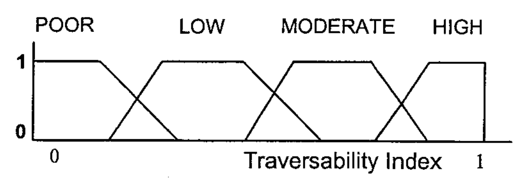


Figure 2. Traversability Index representation

Our approach differs from traditional methods by using a *gradual gradation* of the terrain traversability called the Rule-Based Traversability Index [5]. This Traversability Index is represented by the four fuzzy sets {*POOR, LOW, MODERATE, HIGH*} that correspond to unsafe, moderately-unsafe, moderately-safe, and safe terrain segments respectively (Figure 2). Each terrain segment is assigned a traversability score, which grades the level of risk (or safety) associated with traversing over the given region. As in the traditional methods, the extremes of the multi-valued range are equivalent to regions that are either completely impassable or easily passable. Traversability values in-between these limits correspond to regions with varying degrees of traversal difficulty. Based on this multi-valued representation of terrain traversability, paths are planned to minimize traversal cost. Waypoints through these regions are calculated and sent to a regional terrain assessment algorithm which determines the safest regional segment to traverse based on cameras on-board the robot. During traversal, a local hazard avoidance algorithm ensures that the robot circumnavigates local hazards. It is this multi-resolution approach (global region-based planning and local region assessment) that allows the planner to operate on a minimal representation. That is, given estimates of the regional traversability available at planning time and the finer-grained local sensor-based hazard avoidance at execution time, granularity of the traversability map and associated planning process can be much larger than in traditional obstacle-based planners.

3. Terrain-Based Path Planning

The path planning approach developed here is based on the new concept of Traversability Index. We have developed the terrain-based path planner for mobile robots by integrating two main concepts: traversability map building and global terrain-based path planning (Figure 3).

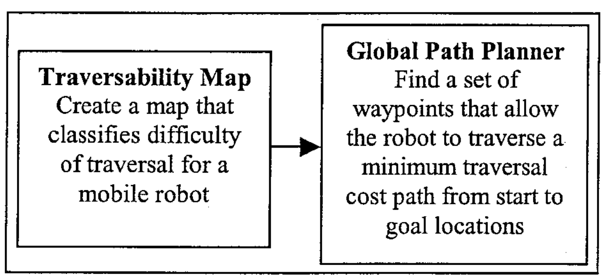


Figure 3: Overview of T* path planning algorithm

The Traversability Map represents the ease-of-traversal of the global terrain. Thus, the traversability map-building process involves identifying major terrain features (such as hills, lakes, valleys) as observed in images obtained during prior aerial imaging or land surveying. These image collections allow for planning at different scales of resolution. This terrain information is passed onto the traversability map-building algorithm, which assigns traversability scores based on terrain characteristics using a fuzzy-logic rule-base [6]. For example, a crater can easily be designated as untraversable, and thus will receive a POOR traversability index, whereas a hill, depending on its slope, may receive any value associated with POOR to MODERATE traversability. A typical rule set will thus be:

IF *Plateau* **is Present** and *Roughness* **is Smooth,**
THEN *Traversability* **is High**

IF *Hill* **is Present** and *Slope* **is Slanted,**
THEN *Traversability* **is Moderate**

IF *Plateau* **is Present** and *Roughness* **is Rocky,**
THEN *Traversability* **is Low**

IF *Crater* **is Present,** THEN *Traversability* **is Poor**

The outcome of this algorithm is the Traversability Map, which is represented by regions of different traversability scores (Figure 4a).

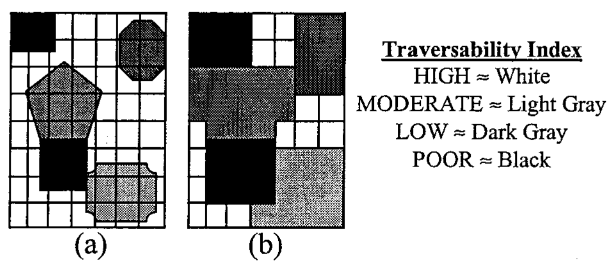


Figure 4. Traversability Map (a) and Grid (b)

A grid map based on the traversability map is then generated in which each grid cell is assigned the *minimum* traversability value of any region enclosed by that cell (Figure 4b). This ensures that a cell is marked untraversable if any part of the cell is untraversable. From this point, a search algorithm is used to find an optimal path from the robot's start position to a designated goal position. In order to enable long-range traverses of mobile robots, the designated path must be implemented in minimum distance (or time) and ensure robot survivability. The inputs to the search algorithm are thus the Traversability Map, the robot's initial position, and desired destination. The output from the algorithm is a set of waypoints designating a minimal traversal cost path from the start position to the goal location.

The focus of the global path planning algorithm is to find a path that minimizes a user-defined traversal cost function. By using a local behavior strategy, the mobile robot can move in its uncertain environment without risk from obstacles or poor traversability regions. Thus, it is not necessary for the global path planner to construct an exact path. Instead, only a sequence of reasonably spaced waypoints is required [7]. Given the robot's initial position and destination, and the traversability grid, an A* search strategy [8] is implemented to determine the sequence of waypoints necessary for path achievement.

A* attempts to find a solution which minimizes the total traversal cost of a solution path by combining the advantages of two search techniques known as *best first* search and *breadth first* search [9]. Breadth first search attempts to find the best path by looking at solutions with minimal cost from the initial start location, whereas best first search attempts to guess at the best optimal solution by using heuristics. The A* search algorithm thus assigns to each possible solution a combination of the cost of the path traversed so far and the estimated cost to the goal solution. A* is classified as a heuristic-based search methodology that searches through the solution space by minimizing a user-defined cost function. Each grid cell represents a possible node to be searched and is given an associated cost value. This cost function is based on maximizing safety (traversability value) and minimizing the path length for goal attainment. For our application, this cost function is defined as:

$$C = \alpha \sum \frac{1}{\tau_i} + \beta \sum l_i$$

where τ_i is the traversability index of cell i, while $1/\tau_i$ represents the cost associated with traversing cell i, and l_i is the distance from the goal cell position to cell i's position in the grid-map. The relative values of α and β represent the aggressiveness of the traversal cost function, where *aggressive* is related to the willingness of the user to take risks. For an aggressive cost function, α is chosen low and β is chosen high; whereas for a conservative function, α is high and β is low.

The rule-base is designed to prefer safe paths. In other words, to arrive at the destination safely is more important than trying to find the shortest path through the terrain. The weights α and β can be adapted based on user constraints. For example, if safety is as equally important as path length, both α and β can be given equivalent weighting values. Under no circumstances though, do we allow the robot to traverse a POOR traversability region in which there is unacceptable risk to the robot. Once a safe path is constructed using the search methodology, waypoints are calculated and sent to the regional terrain assessment algorithm on-board the robot.

4. Path Planner Graphical Simulator

The Path Planning Graphical Simulator is a software tool developed at JPL. It provides an essential tool for visualization and testing of the capabilities offered by the terrain-based path planning method described in this paper. The simulator is written as a Java application for platform independence, and runs on PCs as well as on Sun Unix machines. A snapshot of the graphical interface is shown in Figure 5.

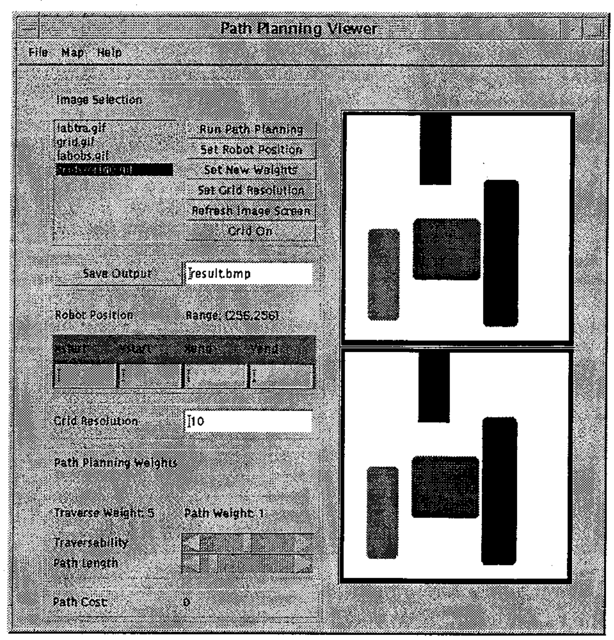


Figure 5. Path planning graphical simulator

The main components of the graphical simulator are:

- A graphical user interface that includes selectable options used by the planner
- A terrain image viewer/editor that displays terrain maps and resulting paths

The first step in the path planning process is selecting a terrain map of interest. Grayscale images are used to represent the traversability values which correspond to terrain features and are denoted using a range of grayscale pixel values. A pixel value of 255 (white) represents a terrain region that is safe for robot traverses, whereas a pixel value of 0 (black) represents terrain that is unsafe, resulting in unacceptable risk to the robot. Values in-between correspond to varying degrees of terrain safety. A user may select different terrain images for path planning purposes using the graphical simulator, or the user may interactively add or remove traversability regions from the displayed image map.

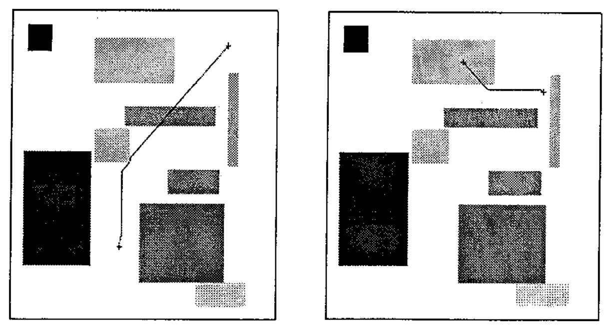
The next step in the process is to populate the user-selectable options, which parameterize the path planner's performance. The selectable options include:

- Set Weights
  - ➢ Select values for the α and β weights used in the cost function mentioned above.
- Set Grid Resolution
  - ➢ Segment the image scene into individual grid cells. The higher the resolution value, the faster the search process.
- Set Robot Positions
  - ➢ Specify robot initial position and destination.

Once all options are entered, the user may run the path planner, at which point the image scene is segmented into individual grid cells using the grid resolution parameter and a cost is associated with each cell. The cost value is then used to find the minimal safest path that links the robot's start and goal positions, after which the path planning results are graphically displayed to the user.

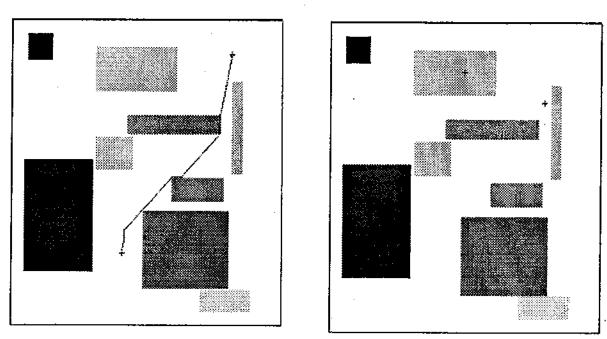
Using the path planning graphical simulator, we have performed computer simulations to compare our algorithm with the classical A* search method. Table I and Figures 6-7 compare sample results from the traditional A* path planning method versus our terrain-based T* path planner.

Observe that in Figures 6a and 7a, most of the path obtained by the T* algorithm differs from the path obtained by the A* algorithm. Figure 6a shows the capability of the T* path planner to compute a path of shorter length than the traditional A* algorithm. In essence, the T* algorithm is able to compute a feasible path which crosses areas that contain acceptable risks, whereas the A* algorithm circumnavigates these regions entirely. Figures 6b and 7b show the extreme situation in which the A* algorithm is unable to find a feasible path because the goal is positioned in a region also occupied by a terrain hazard. In contrast, T* is able to successfully plan a path from the start to goal location based on its ability to deal with the multi-valued representation of the terrain hazards.



(a) (b)

Figure 6. Sample results of T* path planning method



(a) (b)

Figure 7. Sample results of A* path planning

Figures	T* path length	A* path length
a	174	187
b	79	No path found

Table I. Results obtained from comparing T* and A* path planning methods

5. Field Tests

Figure 8 shows snapshots of the field test site used for testing the path planning method with a Pioneer 2AT mobile robot. Figure 9 shows the corresponding traversability map derived from the test site by land surveying. The chosen site covers an area of 29m by 38m and contains regions of rocky hills, steep slopes, and flat sandy zones. In this paper, we present case studies to demonstrate the capabilities of the terrain-based path planning method for mobile robots. The path planning simulation results for these runs are shown in Figure 10 and the corresponding A* runs are depicted in Figure 11.

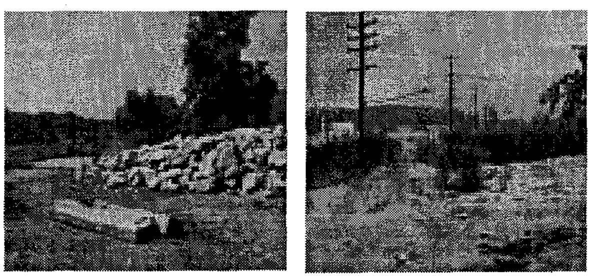


Figure 8. Field test site photos

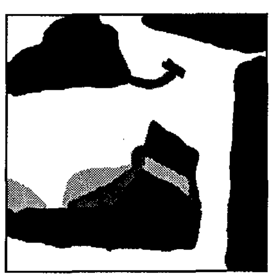
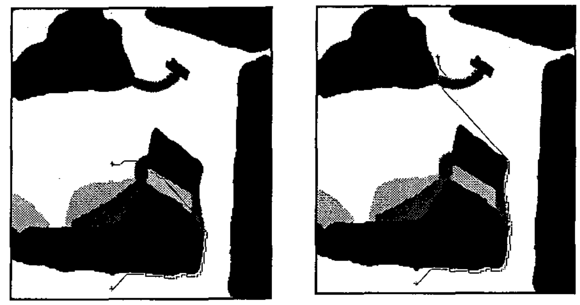
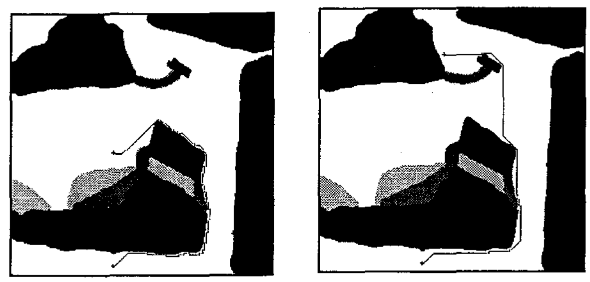


Figure 9. Derived traversability map from land survey



(a) (b)

Figure 10. T* path planning results from case studies



(a) (b)

Figure 11. A* path planning results from case studies

In Figures 9-11, the white, light gray, dark gray, and black regions have HIGH, MODERATE, LOW, and POOR traversability indices respectively. Two case studies are considered. The first case study is shown in Figures 10a and 11a, and the second case is shown in Figures 10b and 11b. By comparing Figures 10a and 11a, it is seen that the path generated by the T* path planner is considerably shorter than that generated by the A* planner. Similar observations can be made by comparing the paths shown in Figures 10b and 11b. We conclude that the use of the multi-valued representation of terrain traversability allows the robot to physically traverse areas which otherwise would be considered untraversable given a binary representation of terrain hazards. In both test cases, the T* algorithm is able to find paths of shorter length than the A* algorithm and is still able to safely reach the goal position. In the field tests (Figure 12), the robot successfully follows the path generated by the T* planner.

Figure 12. A typical field test photo of rover traversal

6. Conclusions

We have presented a novel terrain-based path planner which uses the concept of the traversability map to incorporate terrain characteristics into the path planning process in order to plan safe paths on hazardous terrain. The utilization of the traversability index is shown to provide a natural terrain-based representation, which is necessary for planning safe paths in rough, natural terrain. This framework is particularly suitable for planning paths for planetary robots in that it reduces the computational resources necessary for terrain-based path planning by incorporating a *minimalist* representation of the terrain. This is accomplished by segmenting the global terrain into regions with distinct traversability characteristics, where the region boundaries need not be known accurately. Through experimentation, it is shown that this methodology leads to improved results over the traditional path planning methods. Future work will involve integrations of the planner with regional terrain assessment and local navigation behavior on-board the robot.

7. Acknowledgment

This work was performed at the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration.

8. References

1. Jean-Claude Latombe, *Robot Motion Planning*, Kluwer Academic Publishers, The Netherlands, 1991.

2. H. P. Moravec and A. Elfes, "High resolution maps from wide angle sonars," IEEE International Conference on Robotics and Automation, pp. 116-121, St. Louis, Missouri, 1985.

3. A. Stentz, "Optimal and Efficient Path Planning for Partially-Known Environments," IEEE International Conference on Robotics and Automation, vol. 4, pp. 3310-3317, San Diego, CA, 1994.

4. S.L. Laubach and J.W. Burdick, "An Autonomous Sensor-Based Path-Planner for Planetary Microrovers," IEEE International Conference on Robotics and Automation, vol. 1, pp. 347-354, Detroit, MI, 1999.

5. A. Howard, H. Seraji, E. Tunstel, "A Rule-Based Fuzzy Traversability Index for Mobile Robot Navigation," IEEE International Conference on Robotics and Automation, Seoul, Korea, vol. 1, pp. 3067-3071, May 2001.

6. A. Howard, H. Seraji, "Vision-Based Terrain Characterization and Traversability Assessment," Journal of Robotic Systems, vol. 18, no. 10, pp. 577-587, 2001.

7. D. Z. Chen, R. J. Szczerba, and J. J. Urhan Jr., "Planning Conditional Shortest Paths through an Unknown Environment: A Framed-Quadtree Approach," IEEE/RSJ Intern. Conference on Intelligent Robots and System Human Interaction and Cooperation, vol. 3, pp. 33-38, 1995.

8. P.E. Hart, N.J. Nilsson, and B. Raphael, "A Formal Basis for the Heuristic Determination of Minimum Cost Paths," IEEE Transactions on SSC, vol. 4, pp. 100-107, 1968.

9. E. Rich and K. Knight, Artificial Intelligence, McGraw-Hill, New York, 1991.