Traversable Terrain Modeling and Performance Measurement of Mobile Robots

A. Shirkhodaie, R. Amrani, N. Chawla, and Vicks, T.

Intelligent Tactical Mobility Research Laboratory
Department of Mechanical and Manufacturing Engineering
Tennessee State University
3500 John Merritt Blvd., Nashville, TN 37209

ABSTRACT

In this paper, we have described a technique for terrain traversability assessment modeling of mobile robots operating in natural terrain and presented a fast near-optimum algorithm for autonomous navigational path planning of mobile robots in rough terrain environments. The proposed method is based on visual sensing of terrain salient features and analysis of geo-location coordinates of the salient features. Using an algorithmic image processing technique, both free and obstacles spaces are differentiated and multiple candidate terrain paths are generated for optimization of trajectory terrain path of the robot. The algorithm uses a fuzzy logic terrain classifier to categories different salient features of the terrain. A virtual simulation is developed for terrain perception modeling and verification of generated trajectory path plans of the robot. The developed path-planning algorithm is computationally efficient, and suitable for implementation onboard autonomous robotic systems. Several different terrain conditions have been tested to validate the proposed approach.

KEYWORDS: *Traversable Terrain Modeling, Visual Path Planning, Autonomous Robots, Measure of Performance*

1. INTRODUCTION

Autonomous navigation of outdoor terrain in an active pursuit of department of defense in battlefield reconnaissance and surveillance military operations and NASA in exploration of remote planetary surfaces by robotic rovers. There are a number of challenging issues with outdoor terrain navigation. A robot must have the ability to operation autonomously and intelligently on unstructured terrain with minimal interaction with remote human operators. Robot navigation system must provide sufficient onboard intelligence for long-range traverse in sanding, muddy, rocky, and poorly structured natural terrain, without jeopardizing the robot health and mission failure.

This paper focuses, in particular, on the terrain visual sensing and terrain salient features recognition and characterization. We have described a method for terrain salient features detection using imaging technique and proposed a method for terrain rocks formation modeling. Furthermore, we have presented a method for near optimum visual path planning of mobile robots in natural terrain similar to the planet Mars surface. Section 2 addresses some of the challenges with terrain navigation. Section 3 presents a method for visual terrain sensing and salient feature extraction and recognition. Section 4 discusses a near optimum method for navigation path planning of the robot. Section 5 presents our experimental setup. Finally, section 6 presents the conclusion of this research effort.

2. TERRAIN NAVIGATION

Robot navigation in natural terrain is challenging due to uncertainty in recognition of salient features of the environment. Natural terrain is deceiving, superficial, and complex. Without a good perception model of the environment, a robot cannot reliably navigate a terrain and traverse to its goal successfully. Terrain traversability and path planning of all-terrain robots have been addressed by a number of researchers. Howard et. al., [1] presented a technique for terrain traversability assessment learning for outdoor mobile robot navigating. Using human-embedded logic in real-time, they demonstrated a technique for development of terrain perception based on features extracted from imagery data. In their method, they introduced a fuzzy logic framework and vision algorithms for analysis of terrain. Golda et. al., [2] presented a probabilistic modeling technique suitable for analysis of high-speed rough-terrain mobile robots. They have experimentally shown that their model can accurately predict robot performance in simple, well-known terrain, however, in unstructured environment, their stochastic method performance was degraded. A combination of terrain complexity and unaccountable uncertainty measures were found as leading causes in degradation of their predictive terrain assessment model.

For long-range terrain navigation, accurate maps of the terrain are critical for robot navigation system. Without such maps, a robot may spend much time and energy venturing along what turns out to be a dead end. Olson et. al. [4] developed a method based on visual terrain mapping of Mars rovers. Using a visual stereo imaging fusion technique, they have demonstrated a reliable method for high fidelity terrain mapping and robot world perception modeling. By compiling terrain map images using a system that unified multi-resolution models, they were able to integrate Mars descent and orbital images to obtain 3D terrain maps used by rovers for navigational purposes.

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Autonomous robot navigation in natural terrain can be divided into three closely related tasks: (1) *Route Planning*, (2) *Navigation Planning*, and (3) *Mobility Planning*. As illustrated in Figure 1, in *Route Planning*, objective is that of assessment of the terrain in bulk from a large distance away and deciding on feasible terrain courses that maximize traversability potential of the robot as well as its safety and health. Another objective is to identify pertinent intermediate landmarks. The landmarks are used as waypoints that robot can easily identify along its path and localize itself with respect to them if necessary. A typical route path plan may consist of many waypoints laid out on either an aerial map or a landscape image captured from a ground level, or a series of global position coordinates defined manually. Typical range of applicability of route planning ranges from 10 to 1000's feet or higher.

Navigation planning, on the other hand, can be considered as localization of obstacles, treacherous, hills, and slopes, positive and negative objects. Typical range of applicability of navigational planning varies from 2 to 12 feet for a slow moving robot and to a higher range for a fast speed robot. In navigation planning a set of short traverse path segments from current robot location to next intermediate landmark or the goal are decided. Navigational planning and following are coupled and achieved by means of a map or some model of environment. Localization and navigational error recovery is critical at this phase, in order to keep the robot as close as possible to its designated path or model frame of reference between its intermediate landmarks. Due to loss of environmental details in the field of view, navigational certainty in correct recognition of landmarks tends to diminish with the distance of landmarks from the robot. To keep the navigational certainty under control, typically the range of effectiveness of localization is within a few feet radius from the robot. Depending on the navigational speed of the robot, terrain intricacy, and sensory reliability, this range can be adjusted appropriately.

The purpose of *Mobility planning* is that of describing a set of low-level drive actions that moves the robot through its obstacle terrain while negotiating and/or avoiding obstacles along its path. An important consideration in this phase is the dynamic interaction of the robot with its environment, in particular, detection of robot wheel traction losses during steering while avoiding wheel traps, wheel supports, and tip over states [6]. Another consideration is optimization of robot's safety, energy, and reliability [5]. Typical range of applicability of mobility planning is from a few inches to a few feet depending on physical ability (i.e., wheel diameter) of the robot, and complexity of the terrain. In [6], dynamic modeling of robot and environment is shown reliable for simple, well-characterized terrain. However, on rough terrain, unknown terrain, model fidelity degrades due to imprecise knowledge of terrain parameters.

For terrain navigation, it is very difficult if not possible to obtain a precise mathematical model of the robot's interaction with its environment. Even if the dynamics of the robot itself can be described analytically, the environment and its interaction with the robot through sensors and actuators are difficult to capture in a mathematical sense. The lack of precise and complete knowledge about the environment limits the applicability of conventional control system to the domain of autonomous robotics. If one draws an analogy to navigational skills of animals and humans in nature terrain, they both perform route, navigation, and mobility planning simultaneously and intelligently without getting trapped in the middle of terrain obstacles. Vision plays the most critical role, though physical mobility ability plays an equal important role in achieving navigational mobility objective. This observation motivated what it follows here. In this paper, we have presented an approach that solely relies on visual terrain characterization and intelligent path planning based on localization of salient features of the environment.

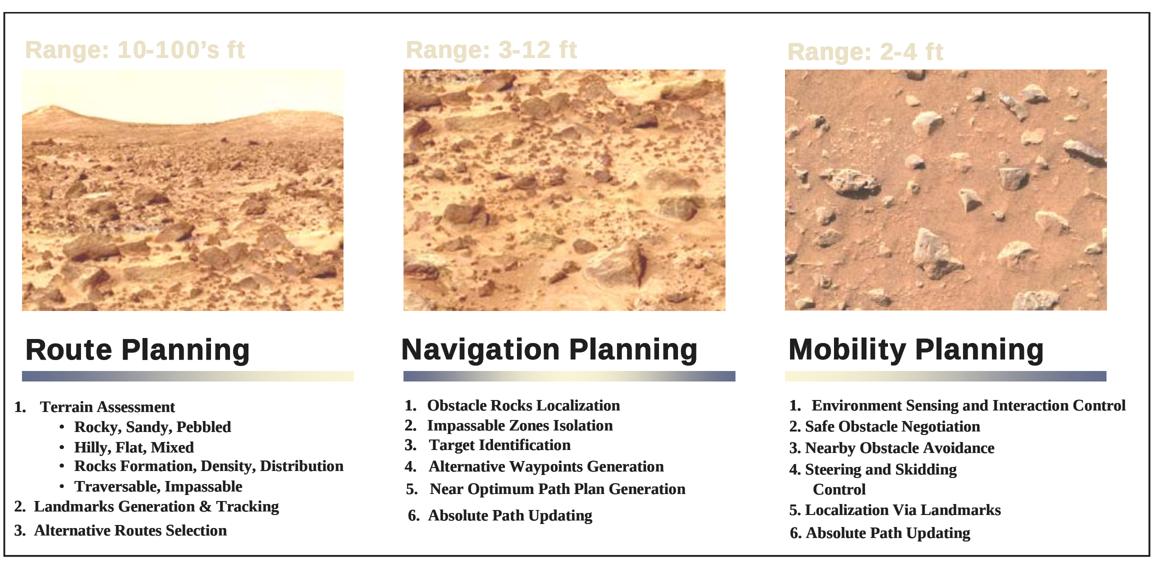


Figure 1. Three Stages of Navigational Path Planning in Natural Terrain

3. TERRAIN PATH PLANNING

The proposed visual navigational path-planning scheme is comprised of three phases. In the first phase, an image of natural terrain is obtained for detection of salient features of the environment. Using imaging techniques, the salient features are isolated and characterized. The environment features we are interested about include: obstacle free areas, rocks formations, sand piles, hills, and slopes. By salient features analysis, we can determine measures characterizing the environment surroundings and classify them appropriately. Furthermore, additional information such as rocks density and geolocation distribution, instable sand piles, and high risks ground conditions (i.e., hills, and slopes) for mobility can be discovered and avoided during navigational path planning of the mobile robot. In the second phase, our algorithm generates a number of waypoints that mark out a near optimum traversable trajectory path for the robot to follow toward its specified target location. In the last phase, a virtual model of the terrain is constructed based on geo-location coordinates and physical attributes of the salient features of the environment. The terrain model serves the robot as a reference model that embeds the robot's state of perception of its surroundings. The terrain model is applicable for simulation verification of robot's generated path plans; in particular, it is appropriate to give the operator tele-presence sense of robot's situation in the remote terrain. Figure 2 presents an example of a rough terrain that our algorithm has analyzed along with the salient features that it has characterized. It also shows a generated world perception model of the rough terrain. The followings present details of this visual terrain traversability assessment technique.

Initially, we divide an image of terrain captured by the robot into a matrix of smaller sub-windows and apply an adaptive binarization technique on each sub-window. This adaptive binarization method locally selects an optimum threshold for binarizing of each sub-window. The resultant binary image is a nonlinear map of geo-location of obstacles in the image frame and thresholds small rocks that are of insignificant size from the background. We explained the non-linearity issue of obstacles geo-location map in next paragraph. The resultant image can now be thought of a binary image where center of each black pixel represents the location of the obstacle centers in the original image. Next, a weight factor is assigned to each black pixels of the resultant binary image. By convoluting the compressed binary image, each black blob cell corresponds to an obstacle center is assigned a weight proportional on number of black blob cells surrounding it. This operation results obstacles appearing farther away from central obstacle receive less or equal weight depending on number of obstacle cell surrounding it. The result of this convolution operation is a hilly field map of the terrain environment. Note that obstacles relative gap from one another in the image frame is not linear. This is due to the fact that obstacles farther away from camera appear compressed in the depth of view. The depth perception diminishes rather

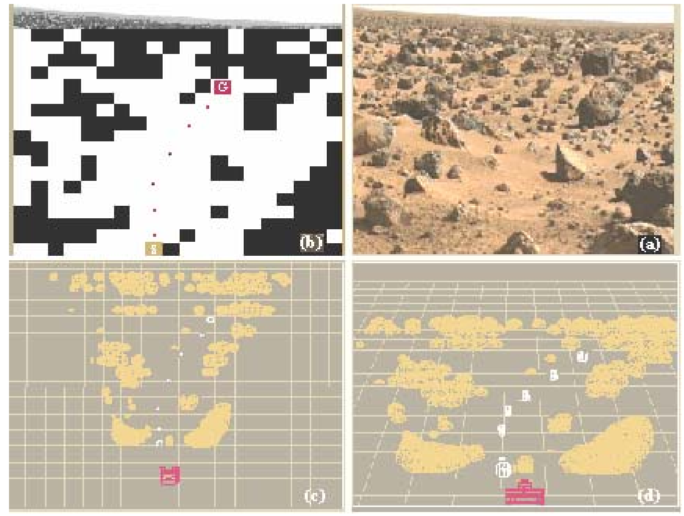


Figure 2. (a) A Rough Terrain, (2) Obstacles Geo-Location Map
(c) Generated Free Path, (d) Close-up View of Generated Free Path

with the square distance of obstacle from the camera. This fact is obvious by observation of Figure 2a. Much wider area of terrain is apparent in the upper part of image than in the lower part of image. Prior to analysis of the image field map, therefore, we map image coordinates of each sub-window to the 3D world coordinate using a camera calibration method described in [7].

Next, we apply a generic algorithm to obtain a free path for the robot among the obstacles. In the generic algorithm, size of the robot is assumed the same size as the width of diagonal distance of terrain area covered by the sub-window in the bottom row of the obstacle geo-location map. Note that physical area represented by image sub-window at upper rows is greater than that of image sub-window at the first row. The generic algorithm is a fast divide-and-conquer approach that searches the obstacle geo-location map row by row. It starts at a row above the first row and at the column where the robot is located. In that row, it searches left and right free spaces to the robot and measures a risk factor for each free space that is proportional to summation of obstacle centers around it. The algorithm determines the most suitable waypoint that minimizes the traveling distance of the robot progressively from start to goal. In an essence, it finds the safest waypoint in the current row that is closest to a straight path connecting the position of the robot to its desirable target location. This optimization method further attempts to intelligently choose a waypoint that is away from any major obstacle along its path. The multi-valued optimization process is carried out layer-by-layer and at each layer through this process a new waypoint is designated for the robot to follow.

Navigation planning is crucial for short-range robot steering. Due to close proximity of robot camera to ground very useful details about salient features of the terrain can be detected at

this stage and characterized with higher degree of confidence. As a robot traverses natural terrain, images may be periodically acquired for traversability assessment. In each period, condition of the terrain can be classified based on the relevant features extracted from the images. One good method of embedding human knowledge is to apply fuzzy logic classification system. Human knowledge can be integrated in terms of knowledge base (i.e., fuzzy rule sets and membership functions). One method also for terrain condition assessment is to perform object surface texture analysis. Objects in different natural terrain have certain distinctive texture properties. The common surface texture attributes include: contrast, variance, energy, entropy, and homogeneity. Image texture is basically due to arrangement of pixel intensities variations that form certain repeated pattern(s). Image repeated patterns are caused by physical surface properties of terrain objects, such as rocks roughness, sand piles waviness, and so on. They could be result of light reflectance from surface of an object. One reliable way to classify textures is to apply quantitative statistics.

An image is a matrix of pixel intensities, $I_{i,j}$. We can define co-occurrence of image matrix as $P_{i,j}$ such as every entry in co-occurrence matrix, $Pd_{i,j}$, is difference in intensity between a pair of image pixels(i and j), that are distance d pixels apart in original image in a given direction. With this notation, the *Energy* associated with an image that is a measure of textural uniformity of an image is defined as:

$$Energy = \sum_i \sum_j P_d^2(i, j) \tag{1}$$

Image Energy reaches its highest value when its image pixel intensity level distribution has either a constant or a periodic form. Furthermore, *Image Entropy* is a measure of disorder of an image and achieves its largest strength when all elements in the *P* are equal. Entropy is inversely proportional to Energy and is defined as:

$$Entropy = -\sum_i \sum_j (i-j)^2 \log P_d(i, j) \tag{2}$$

Image contrast, on the other hand, is a difference of the *P* and it measures the amount of local variation of an image. The image contrast is measured by:

$$Contrast = \sum_i \sum_j (i-j)^2 P_d(i, j) \tag{3}$$

Image homogeneity is inverse different moment measures of image and achieves its largest value when image pixel intensity repetitions are concentrated near the main occurrence matrix diagonal. The image homogeneity is defined as:

In order to minimize the computation requirement, we choose

$$Homogeneity = \sum_i \sum_j \frac{P_d(i, j)}{|i-j|^2}, \qquad (i \neq j) \tag{4}$$

the contrast, variance, and energy texture attributes as basis for terrain surface texture analysis. They provide reliable statistical assessment of a terrain object surface texture, in particular, when small image window are analyzed to assess the terrain condition.

In our approach, we divide a full size terrain image into hundreds of finite (small) sub-windows. For each finite image sub-window, we perform surface texture analysis and apply fuzzy logic rules for classification of the terrain. This process is analogous to stress state analysis of a loaded mechanical part when subjected to Finite Element Analysis (FEA). In a FEA process, stress state of each finite element is individually computed under physical constraints and restriction and then stress states of computed finite elements are aggregated to assess the complete stress state of the object under applied loads. We follow a similar approach. We initially conduct terrain traversability assessment on individual finite sub-windows of image independent of context of the whole image, and then aggregate the results to achieve terrain traversability assessment measures and classifying salient features of the nature terrain vigorously.

This method has two benefits. First, it allows much simpler, yet more inclusive fuzzy rule system to be developed for terrain traversability assessment purposes. Secondly, the method offers an opportunity for performing parallel image processing since each sub-window image can be independently analyzed. This feature can expedite terrain traversability assessment considerably if the robot has onboard parallel computation capability. For development of fuzzy rules and membership functions, we chose a set of natural terrain image samples randomly selected from among many salient features of different terrains. We asked some terrain experts to classify terrain conditions at locations where the finite image sub-windows were taken. In parallel, for each finite image sub-window we computed their corresponding image surface texture properties. We compiled over 200 different natural terrain data patterns. By considering range of texture attributes variation of these sample data, we developed a set of suitable fuzzy logic membership functions and fuzzy rule systems that closely mimic the human expert's judgment of the terrain traversability.

4. TERRAIN TRAVERSABILIY ASSESSMENT ALGORITHM

Table 1 summarizes the algorithm we discussed above. The algorithm performs identification, localization, and recognition of rock formations and generates a collision free traverse path based on the optimization technique discussed earlier in section 3. The algorithm initially enhances the image by removing noises and applies a Canny edge detector to extract out rocks edges. Next, an adaptive binarization convolution method is applied to binarize the image. The result is the blobs of rock formations with enhanced edges.

The algorithm sorts the rock blobs according to their size and ignore the smaller rocks that can be negotiated with the robot during mobility planning phase. The remaining rock blobs are treated as obstacles that the robot needs to avoid. The algorithm computes center location and principle moments of the rock blobs.

The algorithm uses a Fuzzy Logic Terrain Classifier (FLTC) to compute a certainty confidence factor for each detected rock blob. The objective of FLTC is to verify that indeed the detected blob has surface texture similarity close to that of a rock. Using texture analysis method, we compute image intensity contrast, energy, and variance, as well as rock blob area. The first three attributes yield the most consistent indication of the rock texture formation. The last attribute helps with the physical size classification of the rock. The image texture attributes are used as input to the FLTC. Figure 3 presents nine cases by which we geometrically characterize the shape formation of the rocks. Figure 4 presents the fuzzy membership functions corresponding to these image texture attributes. The fuzzy inference engine of FLTC classifies the rocks based on a certainty confident level. Figure 5 illustrates the fuzzy output membership functions considered for this purpose for classification of rock formations. After verification of the rocks, we apply a geometrical analysis scheme to characterize geometrical formation of each detected rock.

<u>Table 1. Algorithm for Terrain Traversability Path Planning and Assessment</u>

1. *Apply a low-pass filter to reduce noise.*
2. *Apply an Adaptive Binarization to binarize the image.*
3. *Apply a blob detector to isolate rocks bigger than a size threshold level.*
4. *Compute texture attributes of next largest rock blob.*
5. *Apply fuzzy logic rock classifier to determine rock detection certainty.*
6. *If rock detection certainty is above a threshold value, compute center location and principle moments of the rock blob; otherwise continue with step 4.*
7. *Characterize and model the rock geometry and log in its coordinates, orientation, and geometrical configuration and dimension; if more rocks are remaining for analysis, continue with step 4.*
8. *Map location of each rock to the world*
9. *Apply the divide-and-conquer collision free traverse pathfinder as described in section 3 to generate near-optimum traversable trajectory paths for the robot.*
10. *Select a feasible trajectory path with the highest measure of traversability.*

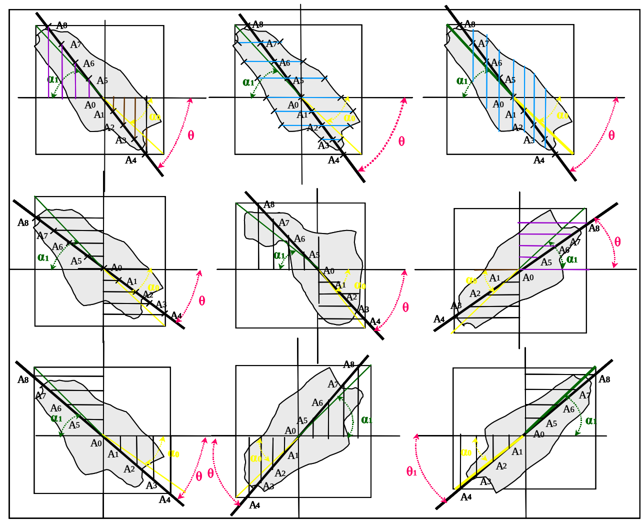


Figure 3. Nine rock formation models and their dimensional measurement probing methods.

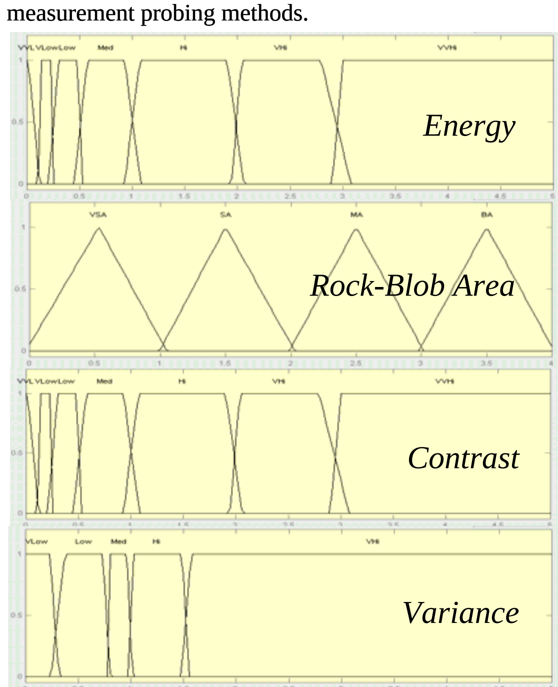


Figure 4. Input Membership Functions of Fuzzy Logic Rock Classifier

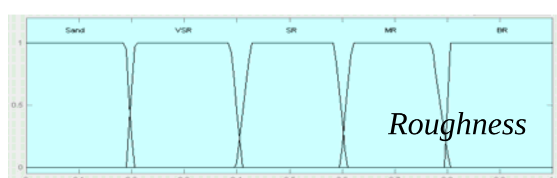


Figure 5. Output Membership Function of Fuzzy Logic Rock Classifier

Of a particular importance is boundary formation of each rock around its first moment axis and mass distribution of the rock around its first moment. Two factors that control the shape appearance of the rock. We model the shape of rocks in our virtual simulation environment using either hemi-spherical or ellipsoidal geometrical representations. We use hemi-spherical rock representation to model that class of rocks appeared to have square dimensional proportionally. For the rocks appeared to have rectangular configuration, however, we use one of the nine models depicted in Figure 3. We construct an ellipsoidal object using a lofting technique applied in CAD software for construction of solid objects. A loft is result of surface formation achieved by connecting contour of several parallel construction polygons together. To model each rock as a loft, we use the first principle moment axis of the rock and create eight spaced, parallel, semi-circles construction polygons with varying diameters proportional to circumferential diameter of the rock in normal direction to its first principle moment axis. Depending on the orientation of the rock's first principle moment axis, the algorithm selects an appropriate rock model representation. The circumferential diameter of the rock is measured in incremental distance along longitudinal direction of the rock's first principle moment axis. Line segments A0 through A8 shown for each rock model in Figure 3 illustrates position and direction of measurement of the rock's circumferential diameters. Measurement is accomplished by image probing along the line segments A_i 's in the binary image. See Figure 6b. In the final step of this algorithm the path planning technique described in section 3 is applied to generate a near optimum free path for the robot. Figure 6 presents terrain modeling and geo-location distribution of rocky surface of a Martian Terrain.

5. PERFORMANCE MEASUREMENT

The proposed terrain traversability assessment method was tested for assessment of several natural terrains. We chose several B/W and Color images taken by Pioneer and Opportunity Mars rovers from Mars terrains. The images were in size 320x240 pixels. We chose square sub-window frames of size 20x20 pixels for terrain assessment sampling. Figure 7 and 8 shows the results analysis of four different types of Marian terrains. The six terrain classifications are performed for each terrain. The classes of sub-terrain conditions that were classified were: (S) sandy, (V) very small rock, (m) rough, (M) very rough, (B) big rocks, and (U) uncertain. The algorithm classifies those areas of terrain that are unknown to its internal fuzzy logic model as "uncertain". Another situation that algorithm classified terrain as uncertain is at the border near to horizon line. Due to loss in depth of view, objects appearing near to horizon line cannot be

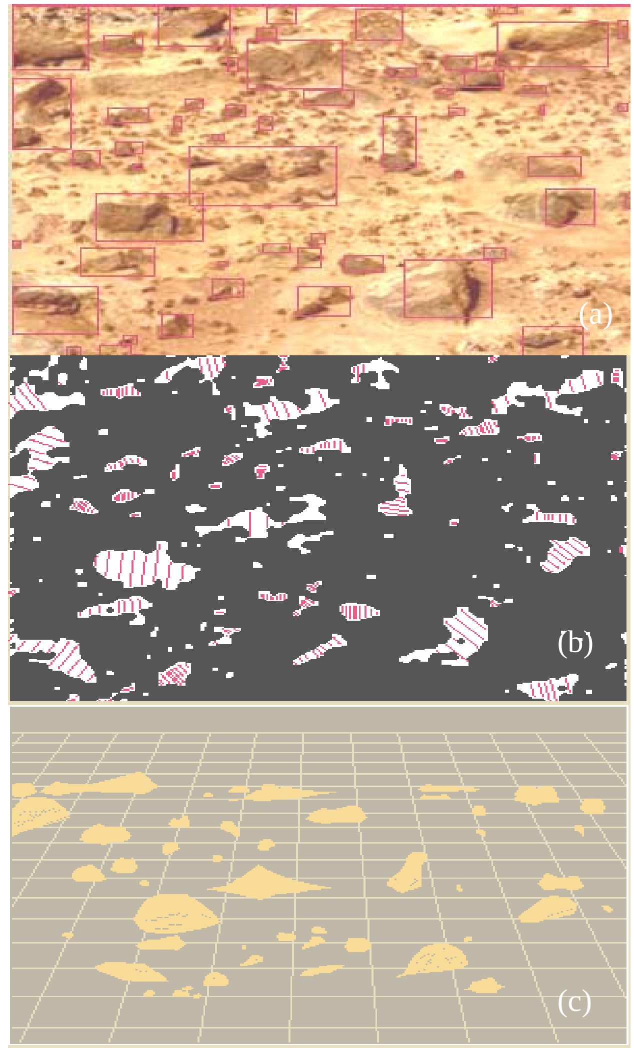


Figure 6. (a) An Image of Mars Terrain, (b) Localized Rock Blobs (c) Modeled Terrain

uniquely differentiated and classified properly. As shown in Figure 7b, the terrain assessment map shows uncertainty about the terrain context at two rows near to horizon line. Depending on pitch angle of the camera, the perception of terrain weakens in the image frame as we move from bottom of the image toward to top. This problem is more severe during route planning phases where the camera is looking directly straight toward the horizon with pitch angle near to zero. However, this problem tends to be troublesome for navigational planning phases (since the camera is pitched more toward the ground and terrain content appears manifestly in the image frame). Notice this observation in Figure 7c. The Terrain Traversability Assessment Measure (TTAM) that we used to evaluate the performance of the fuzzy logic terrain classifier was:

$$TTAM = \frac{\sum_j \sum_i w_{ij} . M_{ij}}{\sum_j \sum_i w_{ij}} \times 100\% \qquad (5)$$

Where, M_{ij} is either 1 when terrain is classified correctly, otherwise 0. w_{ij} is a weight factor that reflects value criticality of terrain classification. It may be assumed flat unity for all different classes of terrain condition, or assigned a range of values based on a degree of belief one may have on reliability of classification of the system. We chose the latter alternative. We selected the range of values of w_{ij} according to the following scheme:

Sandy Terrain:	1.0	Very Rough Terrain:	1.3
Very Small Rocks:	1.0	Rocky Terrain:	1.5
Rough Terrain:	1.2		

5. EXPERIMENTAL SYSTEM SETUP

To experimentally verifying the proposed rock detection techniques and navigational path planning technique, we constructed a terrain mock up similar to Planet Mars surface. Figure 9 presents the physical Mars mock up test bed. The test bed provides a sand pile in size of 16 x 12 feet and rocks of various size and shapes. Our laboratory has several all-terrain robotic platforms. Our robots are equipped with laser scanner, sonar, and stereovision cameras. Many smaller rocks cannot be detected using either laser scanner nor the sonar sensor suit located around the robot since the elevation of the sensors is too high related to the height of the smaller rocks we have. This necessitated usage of camera to visually inspect the rough terrain during navigation.

As a part of this original investigation, we did not employ stereovision capability of our robot, though it is possible to fuse visual and stereovision results to achieve more robust analysis of the terrain [4]. Moving on soft sand pile creates not a major problem for our all-terrain robots. Our robots are relatively heavy and compacts the soil under theirs wheels that results good traction for the robot. They also benefit from all-terrain tire rims that provide a sturdy traction with the ground. However, traction losses become on steep slopes. Due to the later problem, dead-reckoning cannot be respected and visual localization relative to landmarks is a better method for localizing the robot. We are currently implementing the algorithms on our robot supervisory controller called CORMI. CORMI stands for Cooperative Robotic Man-Machine Interface that is developed using FMCell robotic modeling and control software. FMCell provides an intuitive man-machine interface tools for control, sensor and image processing of cooperative robotic systems. Our reference [11] provides a detail description of our Cooperative Robotic Man-Machine Interface (CORMI).

6.

Figure 8. (a) A Mars Terrain, (b) Fuzzy Logic Terrain Assessment Results. The Designation Are: (S) Sandy, (V) Very Small Rocks, (m) Rough Terrain, (M) Very Rough Terrain, (B) Big Rock, (U) Uncertain, (c) Another Mars Terrain, (d) Fuzzy Logic Terrain Assessment Results. Figures (b) and (d) are colored coded.

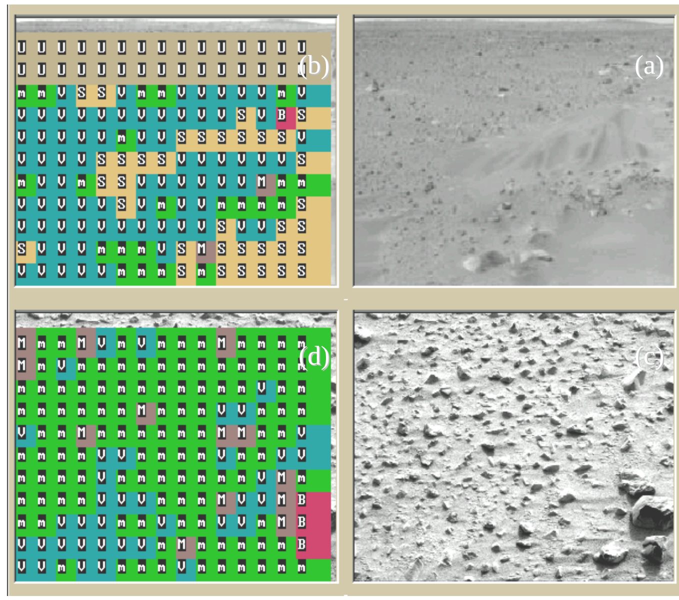
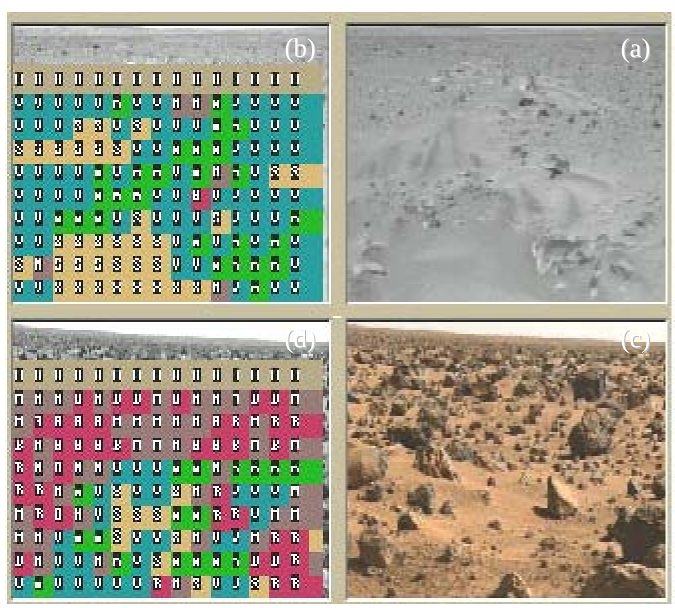


Figure 7. (a) A Mars Terrain, (b) Fuzzy Logic Terrain Assessment Results. The Designation Are: (S) Sandy, (V) Very Small Rocks, (m) Rough Terrain, (M) Very Rough Terrain, (B) Big Rock, (U) Uncertain, (c) Another Mars Terrain, (d) Fuzzy Logic Terrain Assessment Results. Figure (b) and (d) are colored coded.



CONCLUSION

In this paper, we have discussed some of the navigational challenges associated with path planning of mobile robots in natural terrain navigation traversability assessment and presented a method for route planning and navigation planning in rough terrain. The proposed method applies imagery techniques for detection and localization of terrain salient features. For route planning, we have proposed a divide-and-conquer near-optimum path planner method that is both fast and robust in generating collision free trajectory path plans. We have also presented a method for terrain traversability assessment and characterization based on a fuzzy logic approach. Both approaches are fast and can be readily implement onboard mobile robot to assist the robot with terrain path planning and traversability assessment online.

7. ACKNOWLEDGEMENT

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Figure 9. Mars Mockup Arrange at Intelligent Tactical Mobility Research Laboratory at TSU.

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