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Real-Time Assessment of Terrain Traversability for Autonomous Rover Navigation

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Abstract

This paper presents a novel technique for real-time measurement of terrain characteristics and incorporation of this information into the navigation strategy of an autonomous mobile robot. The proposed methodology utilizes a fuzzy logic framework for on-board analysis of terrain traversability, and develops a set of fuzzy navigation rules that guide the rover toward the safest and the most traversable terrain. In addition, a simple goal-seeking behavior is used to drive the rover from its initial position to a user-specified goal position. The overall navigation strategy, consisting of terrain-traverse and goal-seeking behaviors, requires no a priori information about the environment, and uses the on-board traversability analysis to enable the rover to select easy-to-traverse paths to the goal autonomously. The terrain traversability navigation rules are tested and validated with a set of physical rover experiments. These experiments demonstrate the real-time capability of the terrain assessment and fuzzy navigation algorithms.

1. Introduction

Exploration of planetary surfaces by autonomous mobile robots offers several technical challenges. Planetary rovers must have the ability to operate autonomously and intelligently on challenging terrains with minimal interaction with human operators. The rover must have ``on-board intelligence" needed for long-range traverses in highly-unstructured and poorly-modeled natural terrains. Their on-board intelligence must be capable of real-time navigation and motion control based on poor and noisy sensory data. To this effect, the rover must possess the ability to navigate a path to a specified goal, in the presence of sensor uncertainty, while not exposing the rover to any undue risk.

Although considerable research has been conducted on mobile robot navigation in recent years, the bulk of this research is focused on *in-door* robots operating in highly-structured, man-made environments. Typically, the robot's environment consists of a flat, smooth, horizontal floor. On the other hand, planetary rovers must traverse harsh *natural* terrains that are uneven, rough, and rugged. The physical properties of the terrain add a new dimension to the complexity of the robot navigation problem. To ensure mission success, the rover must now incorporate the terrain knowledge directly into its navigation strategy.

To address this issue, an on-board terrain assessment algorithm for mobile robots operating on natural terrains has been developed. Based on the physical properties of the terrain, the suitability of the terrain for traversal is represented using a recently developed fuzzy traversability index [6]. The use of the fuzzy traversability index allows the terrain evaluation algorithm to directly account for sensor uncertainty and noise while still maintaining its robustness. The outcome of the assessment algorithm is directly incorporated into a set of fuzzy navigation rules that guide the rover toward the safest and the most traversable terrain. This rule set is integrated with fuzzy rules for goal seeking to construct an autonomous navigation strategy for a mobile robot that requires no *a priori* knowledge about the environment.

2. Related Work

Few researchers have addressed the inherent problems of mobile robot navigation in challenging terrains. Typically, the traversability of the terrain is defined as an analytical function of the slope and roughness of the terrain and is evaluated at discrete image points [1, 8]. An algorithm is then used to calculate the optimal path through the terrain based on this traversability analysis. In these situations, the navigation strategy does not account for inaccuracies in the sensor data.

In a recent work [2], a search algorithm is used to determine a path from the rover start position to the goal position, while taking into account uncertainty in the terrain data. Although the method is able to effectively plan safe routes through rough terrains, it limits its definition of terrain traversability by solely basing it on terrain "unevenness".

Langer et al [3] focus on computing a list of untraversable regions based on the slope and height of

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points within an image. Terrain is thus classified as either traversable or untraversable, with no variation allowed in this evaluation. This research does not take into account any uncertainty derived from the sensor, beyond the fact that a region is not evaluated if there are not enough elevation points available to determine the slope.

The development of a comprehensive system for robust and safe navigation of planetary rovers operating on challenging terrains has been inadequately addressed in previous research attempts. The following sections address these limitations and describe an autonomous navigation strategy for mobile robots which incorporates real-time terrain assessment algorithms and directly accounts for sensor uncertainty while still maintaining its robustness.

3. Terrain-Based Navigation

In a recent paper [6], the concept of the Fuzzy Traversability Index τ is introduced as a simple measure for quantifying the suitability of a natural terrain for traversal. Two important attributes that characterize the difficulty of a terrain for traversal are the slope and roughness of the region. The Traversability Index can thus be defined in terms of these two physical variables.

3.1 Terrain Roughness

The terrain roughness β is represented by the linguistic fuzzy set *{SMOOTH, ROUGH, ROCKY}*, with the trapezoidal membership functions shown in Figure 1.

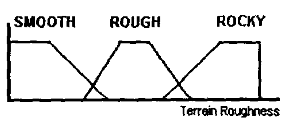

Figure 1. Terrain Roughness fuzzy membership functions

A new approach is developed to determine roughness of a region. First, an algorithm for determining the rock size and concentration of a viewable scene is applied to a pair of stereo camera images. The rock size and concentration parameters are represented in terms of a two-parameter vector $\bar{r} = \{r_{small}, r_{large}\}$, where r_{small} denotes the concentration of small sized rocks and r_{large} represents the concentration of large sized rocks contained within the image. In order to populate the two-parameter vector with numerical values, a horizon-line extraction program is run that identifies the peripheral boundary of the ground plane. This, in effect, recognizes the point at which the ground and the landscaped backdrop intersect. The algorithm then identifies target objects located on the ground plane using a region-growing method. In effect, targets that differ from the ground surface are identified and counted as rocks for inclusion in the roughness assessment. The denser the rock concentration, the higher the calculated roughness of the associated region. Figure 2 shows an example output of the rock identification algorithm.

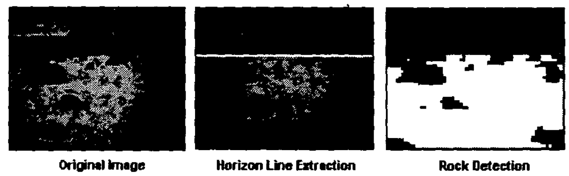

Figure 2. Roughness calculation

To determine the number of small and large sized rocks contained within the image, the number of pixels which comprise a target object are first counted. Those targets with a pixel count less than a user-defined threshold are labeled as belonging to the class of small rocks and those with a count above the threshold are classified as large rocks. This defines the *{SMALL, LARGE}* sets that represent the rock sizes. All such labeled target objects are then grouped in order to determine the small and large rock concentration parameters. This value is then used to populate the two-parameter vector $\bar{r}$ which is characterized by the trapezoidal linguistic fuzzy set *{FEW, MANY}* and used as input into the fuzzy rules summarized in Table I. The terrain roughness is thus derived directly from the rock size and concentration parameters of the associated image scene using Table I.

ROCK CONCENTRATION \ ROCK SIZE	SMALL	LARGE
FEW	SMOOTH	ROUGH
MANY	ROUGH	ROCKY

Table I. Fuzzy rules for Roughness

3.2 Terrain Slope

The terrain slope α is represented by the linguistic fuzzy set *{FLAT, SLOPED, STEEP}*, with the trapezoidal membership functions shown in Figure 3.

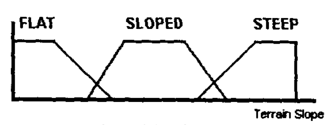

Figure 3. Fuzzy membership functions for Terrain Slope

To obtain the slope from a pair of stereo camera images, we must first calculate the real-world Cartesian *x,y,z* components of the ground plane boundary. We can determine the average slope value using the following equation:

$$slope = \frac{1}{N}\sum_{i}^{N} atan2(z,x) \qquad (1)$$

where N is the number of horizon-line points viewable in both images.

To determine the x,y,z components of the horizon-line, Tsai's camera calibration model [9] is used to derive the relationship between camera image and real-world object position for a single camera. The images from both cameras are then matched in order to retrieve 3D information.

Figure 4. Determination of correlated image points

Given a pair of stereo camera images, correlated image points that lie along the horizon-line are first extracted from each camera image. Determining the position of the largest rocks located along the horizon line and centered within both images allows the identification of correlated image points (Figure 4). These image points are then used as input for extraction of the (x,y,z) real-world Cartesian components as follows:

- $\forall Heights: z=\{0,Z\}$, Convert Image Points to Cartesian
  - $(i_0, j_0, k_0) \Rightarrow (x_0, y_0, z_0)$
  - $(i_1, j_1, k_1) \Rightarrow (x_1, y_1, z_1)$
- Loop through Cartesian Pairs to Find Match, s.t.
  - $\min(\sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2 + (z_0 - z_1)^2}$
- Store Matched Cartesian Point
  - $(x,y,z) = \frac{1}{2}(x_0 + x_1, y_0 + y_1, z_0 + z_1)$

Once all Cartesian points are calculated, they are input into equation 1 for slope determination.

3.3 Traversability Index

Once the slope and roughness parameters are calculated, the Traversability Index τ is computed in order to classify the ease of terrain traversal. The Traversability Index τ is represented by the linguistic fuzzy set *{LOW, MEDIUM, HIGH}*, with the trapezoidal membership functions shown in Figure 5. The Traversability Index τ is defined in terms of the terrain slope α and the terrain roughness β by a set of simple fuzzy relations summarized in Table II.

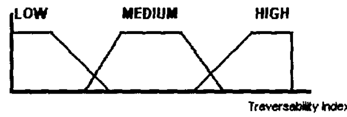

Figure 5. Fuzzy membership functions for Traversability

ROUGHNESS \ SLOPE	FLAT	SLOPED	STEEP
SMOOTH	HIGH	MED	LOW
ROUGH	MED	LOW	LOW
ROCKY	LOW	LOW	LOW

Table II. Fuzzy rules for the Traversability Index

4. Terrain-Based Navigation Rules

The problem considered in this section is to *safely* navigate a rover from a known initial position to a user-specified goal position. The control variables of the rover are the translational speed v and the rotational speed ω. The rover translational speed v is represented by the linguistic fuzzy set *{SLOW, MODERATE, FAST}*, with the triangular membership functions shown in Figure 6. Similarly, the rover rotational speed ω is represented by the linguistic fuzzy set *{LEFT, ON-COURSE, RIGHT}*, with the triangular membership functions shown in Figure 6.

The utilization of the Traversability Index allows the terrain characteristics to be directly incorporated into the navigation strategy. The basic idea behind the terrain-based navigation rules is that the rover tries to:

- Rotate to face the safest and most traversable region.
- Adjust rover speed based on the quality of the terrain to be traversed in order to ensure rover safety and avoid damaging the rover.

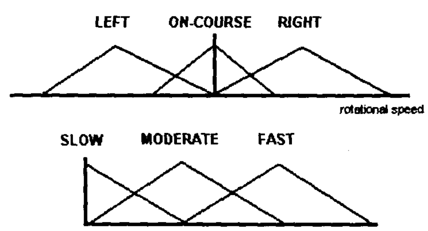

Figure 6. Fuzzy membership functions for rotational and translational speeds

4.1 Turn Rules

The terrain in front of the rover is partitioned into three 60° sectors covering a distance of up to about 10 meters in range (Figure 7). The Traversability Indices for these regions are computed from the measurements of the terrain slope and roughness as described above. The on-board software then uses the fuzzy rule set to compute the three traversability measures and to select the most traversable region.

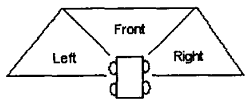

Figure 7. Partitioning of traversability regions

Let τ_f, τ_l, and τ_r represent the Traversability Indices of the front, left, and right sectors, respectively. The six rotational speed rules are then derived as follows:

- IF τ_f is NOT HIGH AND τ_l is HIGH, THEN ω is LEFT.
- IF τ_f is NOT HIGH AND τ_l is LOW AND τ_r is HIGH, THEN ω is RIGHT.
- IF τ_f is NOT HIGH AND τ_l is MEDIUM AND τ_r is HIGH, THEN ω is RIGHT.
- IF τ_f is LOW AND τ_l is MEDIUM AND τ_r is LOW, THEN ω is LEFT.
- IF τ_f is LOW AND τ_l is MEDIUM AND τ_r is MEDIUM, THEN ω is LEFT.
- IF τ_f is LOW AND τ_l is LOW AND τ_r is MEDIUM, THEN ω is RIGHT.

These rules allow the rover to turn toward the most traversable terrain during the navigation process.

4.2 Move Rules

Once the direction of traverse is chosen based on the relative values of τ, the rover speed v can be determined based on the value of the Traversability Index τ^* for the *selected* sector. This determination is formulated as a set of three simple fuzzy rules as follows:

- IF τ^* is LOW, THEN v is SLOW.
- IF τ^* is MEDIUM, THEN v is MODERATE.
- IF τ^* is HIGH, THEN v is FAST.

In the next sections, the goal-seeking navigation behavior and the behavior integration scheme shall be discussed.

5. Goal-Based Navigation Rules

In this section, we present fuzzy rules for navigation of the robot from its current position to the desired goal position. Two sets of rules are developed for the robot translational speed v and rotational speed ω. The basic idea behind the navigation rules is that the robot tries to: (1) approach the goal with a speed proportional to the distance between the current position and the goal position, defined as the "position error" d, (2) rotate toward the goal position by nullifying the "heading error" ϕ, which is the angle by which the robot needs to turn to face the goal directly.

The fuzzy rules for the rover turn rate are as follows:

- IF ϕ is GOAL-LEFT, THEN ω is LEFT.
- IF ϕ is GOAL-FRONT, THEN ω is ON-COURSE.
- IF ϕ is GOAL-RIGHT, THEN ω is RIGHT.

The fuzzy rules for the rover speed are as follows:

- IF d is VERY NEAR, THEN v is SLOW.
- IF d is NEAR, THEN v is MODERATE.
- IF d is FAR, THEN v is FAST.

where {*GOAL-LEFT, GOAL-FRONT, GOAL-RIGHT*} and {*VERY NEAR, NEAR, FAR*} are fuzzy sets representing ϕ and d, respectively.

A more detailed analysis of the goal-seeking fuzzy navigation rules is given in [7].

6. Behavior Integration

Once the recommendation from the terrain-based navigation algorithm is generated, it must be integrated with the goal-seeking recommendation to form a unified autonomous navigation strategy. This task is accomplished by using appropriate weighting factors to generate the combined, coordinated control actions for the rover navigation.

Each behavior generates a set of independent recommendations for the translational speed v and rotational speed ω. These sets of recommendations are denoted by v^t, ω^t, v^g, and ω^g where t and g refer to the terrain-traverse and goal-seeking behaviors, respectively. Once generated, these recommendations are "weighted" by the crisp weighting factors t^w and g^w discussed below. Mathematically, the final control actions are computed using the Center-of-Gravity defuzzification method [5] as:

$$\overline{v} = \frac{t^w \sum v_p^t A_p^t + g^w \sum v_p^g A_p^g}{t^w \sum A_p^t + g^w \sum A_p^g}$$

$$\overline{\omega} = \frac{t^w \sum \omega_p^t B_p^t + g^w \sum \omega_p^g B_p^g}{t^w \sum B_p^t + g^w \sum B_p^g}$$

In the above equations, v_p is the translational speed peak value, A_p is the truncated area under the velocity membership function, ω_p is the rotational speed peak value, and B_p is the truncated area under the rotational speed membership function.

The weighting factors t^w and g^w represent the strengths by which the terrain-traverse and goal-seeking recommendations influence the final control actions $\overline{v}$ and $\overline{\omega}$. Two sets of weight rules for the two behaviors are used. The terrain-based weight rules are as follows:

- IF τ^* is LOW, THEN t^w is HIGH.
- IF τ^* is NOT LOW, THEN t^w is NOMINAL.

The goal-seeking weight rules are as follows:

- IF d is VERY NEAR, THEN g^w is HIGH.
- IF d is NOT VERY NEAR, THEN g^w is NOMINAL.

where {*NOMINAL, HIGH*} are the fuzzy sets representing the weighting factors.

As presented, the proposed autonomous navigation strategy incorporates on-board terrain assessment algorithms and directly accounts for sensor uncertainty and noise while maintaining its robustness. The next section discusses the physical rover experiments used to test and validate the terrain-based navigation rules described above.

7. Rover Experimentation

Figure 8. Pioneer AT Mobile Robot with enhancements

Physical experiments using the Pioneer AT (All-Terrain) Mobile Robot are used to test the reasoning and decision making capability provided by the terrain-based navigation behavior. A trailer is fabricated in-house and is attached to the back of the Pioneer to carry the on-board computer chassis and a second battery. Figure 8 shows the enhanced Pioneer, together with on-board processing capability, two 4-input framegrabber boards, and six CMOS NTSC video cameras. Figure 9 shows the physical layout of the camera platform. The cameras are placed such that the lens centers are 740mm above the ground, the optical axis of each camera is tilted down by 8°, and the intersecting origin of all cameras is centered above the rover wheels. In addition, the stereo baseline length is set to 500mm. This camera placement scheme provides the rover a viewable distance of about 10 meters.

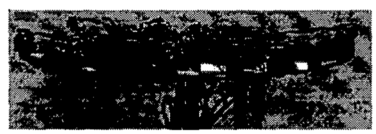

Figure 9. Camera platform for real-time terrain assessment

The processing power on-board the rover consists of a 333 MHz Pentium II processor housed in a CompactPCI chassis running the Linux Operating System. Resident on the computer are the image processing algorithms and the fuzzy computation engine used to calculate the translational and rotational speed commands sent to control the wheel motors. An external laptop computer, running Linux, is linked to the rover through an RF modem pair. The laptop allows the user to specify desired goal positions for the rover.

Using this hardware platform, physical rover experiments are performed in the JPL Mars Yard to simulate planetary-like terrain conditions. The real-time terrain assessment algorithm involves using three pairs of stereo images representing a 180° field of view and possessing the ability to process terrain quality information at a distance of up to 10 meters in front of the vehicle. Figure 10 shows a typical panoramic image of the three stereo pairs with the left, front and right views of the panorama shown from left to right.

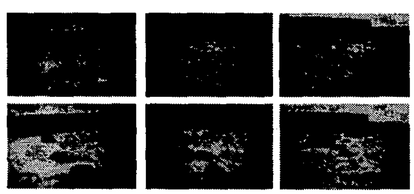

Figure 10. Image sets from three on-board stereo cameras

Each pair of stereo images is input into the slope and roughness image processing algorithms described above. Once the terrain characteristics are extracted, the outcome is used for evaluating the Traversability Index for each region. As shown in Figures 11-12, the safest traversable region for the rover is chosen by the system for traversal. Tables III-IV show the calculated traversability parameters and the translational output values determined from the terrain-based assessment and navigation rules.

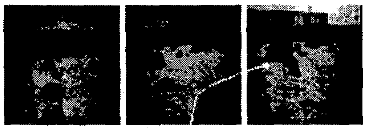

Figure 11. Case study one

Figure 12. Case study two

8. Conclusions

This paper presents methods for real-time assessment of natural terrains for mobile robots. The information regarding the terrain characteristics is incorporated into the navigation strategy of an autonomous mobile robot operating on natural terrains. The implementation of the fuzzy logic methodology and on-board terrain assessment algorithm is shown to provide a natural framework for representing the characteristics of the terrain. Through experimentation, it is shown that the integration of fuzzy rules for terrain-traverse and goal-seeking allows the construction of an autonomous navigation strategy for a mobile robot that requires no *a priori* knowledge about the environment. Future research will be focused on integrating a fuzzy-based real-time collision avoidance algorithm into the complete navigation strategy and performing several field testings.

	Left	**Front**	**Right**
Slope	LOW	LOW	LOW
Roughness	ROUGH	SMOOTH	ROUGH
Traversability	MED	HIGH	MED
Velocity	FAST		

Table III. Case Study One

	Left	**Front**	**Right**
Slope	LOW	LOW	LOW
Roughness	ROUGH	ROUGH	ROUGH
Traversability	MED	MED	MED
Velocity	MODERATE		

Table IV. Case Study Two

Acknowledgments

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