Behavior-Based Robot Navigation on Challenging Terrain: A Fuzzy Logic Approach

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***Abstract*—This paper presents a new strategy for behavior-based navigation of field mobile robots on challenging terrain, using a fuzzy logic approach and a novel measure of terrain traversability. A key feature of the proposed approach is real-time assessment of terrain characteristics and incorporation of this information in the robot navigation strategy. Three terrain characteristics that strongly affect its traversability, namely, roughness, slope, and discontinuity, are extracted from video images obtained by on-board cameras. This traversability data is used to infer, in real time, the terrain Fuzzy Rule-Based Traversability Index, which succinctly quantifies the ease of traversal of the regional terrain by the mobile robot. A new traverse-terrain behavior is introduced that uses the regional traversability index to guide the robot to the safest and the most traversable terrain region. The regional traverse-terrain behavior is complemented by two other behaviors, local avoid-obstacle and global seek-goal. The recommendations of these three behaviors are integrated through adjustable weighting factors to generate the final motion command for the robot. The weighting factors are adjusted automatically, based on the situational context of the robot. The terrain assessment and robot navigation algorithms are implemented on a Pioneer commercial robot and field-test studies are conducted. These studies demonstrate that the robot possesses intelligent decision-making capabilities that are brought to bear in negotiating hazardous terrain conditions during the robot motion.**

***Index Terms*—Behavior-based navigation, fuzzy logic, mobile robots, robot navigation, rough terrain, sensor-based navigation, traversability.**

I. Introduction

HUMANS have a remarkable capability to perform a wide variety of physical and mental tasks without any explicit measurements or computations. Examples of everyday tasks are parking a car, driving in city traffic, playing golf, cooking a meal, and summarizing a story. In performing such familiar tasks, humans use *perceptions* of time, distance, speed, shape, and other attributes of physical and mental objects [1]. Reflecting the bounded ability of the human brain to resolve detail, perceptions are intrinsically imprecise. Perceptions are well beyond the reach of traditional methods, which are based on mathematical modeling and analysis. Instead, perceptions are described by propositions drawn from a natural language, in which the boundaries of perceived classes are fuzzy. For instance, a human can drive a car off-road on a rough terrain using perceptions of the physical environment, rather than with exact information about locations and sizes of objects therein. The driver adjusts the speed and steering of the car based on his subjective judgment of the surface conditions, e.g., the car speed is decreased in off-road driving on a bumpy and rough terrain, but is increased on a smooth and flat surface. The human driving actions are motivated by *perceptions* of the terrain quality and obstacles, and not by explicit modeling and analysis of the surface conditions. It is highly desirable to capture the expertise of the human driver and to utilize this knowledge to develop autonomous navigation strategies for mobile robots. Fuzzy logic provides a means toward accomplishing this goal.

The theory of fuzzy logic systems is inspired by the remarkable human capability to operate on and reason with perception-based information [2], [3]. Rule-based fuzzy logic provides a scientific formalism for reasoning and decision making with uncertain and imprecise information. Fuzzy logic provides a formal methodology for representing and implementing the human expert's heuristic knowledge and perception-based actions. Using the fuzzy logic framework, the attributes of human reasoning and decision making can be formulated by a set of simple and intuitive *IF (antecedent)–THEN (consequent)* rules, coupled with easily understandable and natural *linguistic* representations. The linguistic values in the rule antecedents convey the imprecision associated with the perceptions, while those in the rule consequents represent the vagueness inherent in the reasoning processes. In other words, fuzzy rule-based systems generate actions based on perceptions. The operational strategies of the human expert driver can be transferred via fuzzy logic to the robot navigation strategy in the form of a set of simple conditional statements composed of linguistic variables. These linguistic variables are defined by fuzzy sets in accordance with user-defined membership functions. The main advantages of a fuzzy navigation strategy lie in the ability to extract heuristic rules from human experience, and to obviate the need for an analytical model of the process.

The natural appeal of fuzzy logic to robot navigation has motivated considerable research in this area in recent years (see [4]). Most of this research, however, has been focused on *indoor* mobile robots that operate in highly structured or otherwise *man-made* environments. These environments typically consist of smooth horizontal floors, walls, and known man-made obstacles. In recent years, there has been a growing interest in the navigation of *field* mobile robots that operate on unknown and uncharted *natural* terrain. There are several application domains,

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both terrestrial and in space, which have strongly motivated this research. For instance, NASA has planned an ambitious set of missions to Mars that will carry mobile robots (rovers) to explore the Martian surface and to carry out *in situ* science missions. Similarly, the US Department of Defense (DOD) is sponsoring several research projects that involve autonomous mobile robots operating on rough natural terrain. However, despite widespread applications of outdoor navigation, there are few existing methods for field robot navigation that consider the terrain characteristics [5]–[15]. In the existing methods, terrain traversability is often defined as an analytical function of the terrain slope and roughness. The slope is determined by finding the least-squares fit of a geometric plane covering the region, while the roughness is calculated as the residual of the best-plane fit. Once the traversability of each region is found, a traversable path for the robot is then constructed.

This paper develops a new approach for robot navigation on challenging terrain using a perception-based linguistic framework. Robot navigation is accomplished using fuzzy logic rule statements, as an alternative to conventional analytical methods. The premise of the proposed approach is to embed the human expert's heuristic knowledge into the mobile robot navigation strategy using fuzzy logic. The proposed approach is highly robust in coping with the uncertainty and imprecision that are inherent in sensing and perception of natural environments. The robot navigation strategy developed here is comprised of three independent behaviors, regional traverse-terrain, local avoid-obstacle, and global seek-goal, that recommend motion commands for the robot. The recommendations of these behaviors are then integrated with adjustable weighting factors to yield an autonomous navigation strategy for the mobile robot that requires no *a priori* information about the environment.

The paper is organized as follows. Some of the existing navigation methods are reviewed in Section II. The robot navigation architecture and elemental behaviors based on terrain, obstacle, and goal information are presented in Sections III–VI. The integration of these behaviors into a unified robot navigation strategy is discussed in Section VII. Section VIII summarizes the key attributes of the proposed approach and compares it with existing methods. Section IX describes the implementation of the navigation strategy on a commercial mobile robot, and presents field-test studies that demonstrate the intelligent navigation capability of the robot on challenging terrain. Finally, Section X gives a brief conclusion.

II. Review of Existing Navigation Methods

In this section, we review some of the existing methods for robot navigation on natural terrain. Lacroix *et al.* [5] execute the navigation behavior based on terrain quality. The terrain is classified in four distinct categories: flat, uneven, obstacle, and unknown. Based on three–dimensional image data, the terrain is segmented into cells, and each cell is labeled based on different terrain characteristics such as point density, altitude, and mean vector. A Bayesian classification methodology is employed, in which an estimate of the probability for each label is determined from prior learning, based on prototypes classified by humans.

Simmons *et al.* [6], Goldberg *et al.* [7], and Singh *et al.* [8] compute an analytical traversability measure for the terrain, based on stereo range data. Roll, pitch, and roughness of terrain cells are estimated from the viewable terrain image. Roll and pitch are calculated by using a least-squares method to fit a plane to the range data, and roughness is computed as the residual of the fit. These measures are normalized in the range [0,1] and a goodness value is determined, based on the minimum value of the three parameters. A certainty factor is also calculated as a function of the number and distribution of range points within a cell. A path planner then evaluates the traversability along predetermined candidate paths by taking a weighted combination of the goodness and certainty values. Votes for each path are then sent to an arbiter that determines the best path to traverse.

Langer *et al.* [9] focus on the development of a navigation system that generates recommendations for vehicle steering, based on the distribution of untraversable terrain regions. Traversability is determined by combining elevation and slope information to classify cells as obstacles. Those cells having slope values above a given threshold are classified as untraversable. Cells without enough range information are not classified, allowing the rover to approach these areas and retrieve additional information if necessary. Based on the location of obstacle cells, a steering command is generated by combining votes from multiple behaviors and deciding on the best command. Votes are given continuous values between -1 and $+1$ based on the height and position of obstacle points located within the image.

Finally, Gennery [10] uses estimates for slope and roughness at equally spaced grid points to compute a cost function for traversability. Slope is computed by fitting a weighted least-squares plane to a height map, and using the residual of the fit to estimate roughness. An analytical function representing the cost of driving over each grid point is then calculated, based on the probability that the slope and roughness are less than maximum threshold values. This probability of traversability is approximated based on a Gaussian error distribution.

III. Structure of Behavior-Based Navigation Strategy

In behavior-based robot navigation systems, goals are achieved by subdividing the overall task into small independent behaviors that focus on execution of specific subtasks. For example, a behavior can be constructed which focuses on traversing from a start to a goal location, while another behavior focuses on obstacle avoidance. The basic building block of the proposed navigation strategy is a *behavior*. In our strategy, each behavior is composed of a set of fuzzy logic rule statements aimed at achieving a given desired objective. There are two types of rules for each behavior, *navigation* rules and *weight* rules. The navigation rules consist of a set of fuzzy logic rules for robot translation and rotation of the form

$$\text{IF } C, \text{ THEN } A \tag{1}$$

where the *condition* C is composed of fuzzy input variables and fuzzy connectives (AND, OR, NOT) and the *action* A is a fuzzy output variable (see Sections IV–VI). Equation (1) represents the general form of a typical rule in a set of natural *linguistic* rules. This is analogous to the actions taken by an expert human driver based on the prevailing conditions, e.g., from a safety perspective, IF *road* is *icy*, THEN *speed* is *slow*. The output of each behavior is a recommendation over all possible motion commands from the perspective of achieving that behavior's objective. Multiple behaviors can be active simultaneously in the navigation strategy, each aimed at achieving one specific subgoal. Integration of multiple behaviors is implemented by combining the outputs (recommendations) of all active behaviors using their weight rules. For each behavior, the weight rules consist of a set of fuzzy logic rules for weight assignment of the general form

$$\text{IF } S, \text{THEN } W \tag{2}$$

where S is a logical statement describing a physical *situation*, and W represents a fuzzy expression of the *weighting factor* with which that behavior's recommendation is considered in the prevailing situation (see Section VII). For instance, for the safety behavior of the human driver, IF *sunlight* is *low*, THEN *safety weight* is *high*. For each behavior, the recommendation of navigation rules is scaled by the gain obtained from the weight rules. The weighted combination of all the behaviors' recommendations is then defuzzified and issued as a command to the mobile robot wheel actuators for execution. Equations (1) and (2) represent a framework for embedding the human expert's knowledge into the robot navigation strategy.

The robot navigation strategy proposed in this paper is comprised of three simple behaviors. These behaviors operate at three different ranges, with the seek-goal behavior at *global*, the traverse-terrain behavior at *regional* and the avoid-obstacle behavior at *local* ranges. Note that the new regional traverse-terrain behavior introduced in this paper complements the local avoid-obstacle and global seek-goal behaviors commonly used in behavior-based navigation systems. We shall now describe the three elemental behaviors.

IV. Regional Traverse-Terrain Behavior

The problem addressed in this section is to navigate a mobile robot to the safest and most traversable region of a natural terrain. The section is comprised of two parts. In the first part, a perception-based traversability index is inferred for each terrain region, based on real-time assessment of the terrain quality extracted from on-board sensory data. In the second part, a new technique for terrain-based navigation is developed, in which the terrain traversability index is used directly in the robot navigation logic so as to guide the robot toward the most traversable terrain. The terrain assessment and robot navigation rules represent, respectively, the visual judgment and driving actions of a skillful human driver operating the vehicle.

A. Real-Time Terrain Assessment

In recent papers [16], [17], the concept of *Fuzzy Rule-Based Traversability Index* is introduced as a simple measure for quantifying the suitability of a natural terrain region for traversal by a mobile robot. Three important attributes that characterize the difficulty of a terrain region for traversal are the roughness, slope, and discontinuity of that region. A subsequent paper [18] documents the process for extracting these characteristics from imagery data obtained from cameras mounted on the robot. These characteristics are represented in a fuzzy logic framework, using perception-based linguistic fuzzy sets, and are used to infer the Fuzzy Rule-Based Traversability Index.

1) Terrain Characterization: Unlike existing methods that compute the terrain roughness analytically as the residual of the best-plane fit, the measure of terrain roughness proposed here is based on the sizes and concentrations of rocks in a viewable image scene using simple linguistic rules [18]. The proposed approach is perception based, and is analogous to the human observer's visual judgment of terrain roughness. An object in the terrain image is classified as a rock if its characteristics differ from the ground surface[1]. The rock-detection algorithm identifies rock objects located on the ground plane, and determines the sizes and concentrations of rocks contained within the image. This information is then converted into the {SMALL, LARGE} fuzzy sets for rock size, and {FEW, MANY} fuzzy sets for rock concentration. The terrain roughness is represented by the three linguistic fuzzy sets {SMOOTH, ROUGH, ROCKY}, and is derived directly from the rock size and concentration parameters of the associated image scene using the following intuitive rule set:

1) IF S is SMALL AND C is FEW, THEN β is SMOOTH;
2) IF S is SMALL AND C is MANY, THEN β is ROUGH;
3) IF S is LARGE AND C is FEW, THEN β is ROUGH;
4) IF S is LARGE AND C is MANY, THEN β is ROCKY;

where S is the rock size, C represents the rock concentration, and β denotes the corresponding terrain roughness. The membership functions for the three fuzzy roughness classes are shown in Fig. 1(a). Note that multiple rules can be active at the same time. To further ensure that this approach gives a perceptual, linguistic definition of terrain roughness as used by a human observer, an optimization technique can be applied that adjusts the membership function parameters based on the perceptual performance of a human expert [19]. This process is accomplished by having human experts classify the roughness characterizing various terrain image scenes by visual examination. In this way, the human expert acts as a supervisor to teach the fuzzy terrain classifier to mimic human visual perception.

We define slope as the inclination of the ground plane with respect to the robot's current angular tilt. To determine this lateral slope parameter, an approach [18] is used to obtain elevation information from two uncalibrated cameras. The process involves training an artificial neural network to learn the relationship between slope and coordinates of correlated points within a terrain image. The network is trained on typical imagery data representing different positive and negative sloped surfaces. Points located on the ground plane at a position furthest from the robot are extracted from multiple images and fed as inputs into the network. The network is then trained by finding a set of weights that produce the desired slope output, given the set of data input values. Once the learning process is completed, it is utilized to extract the slope during run time. The output of the network

[1]The term *rock* is used here in the generic sense to imply both positive obstacles (rocks) and negative obstacles (ditches).

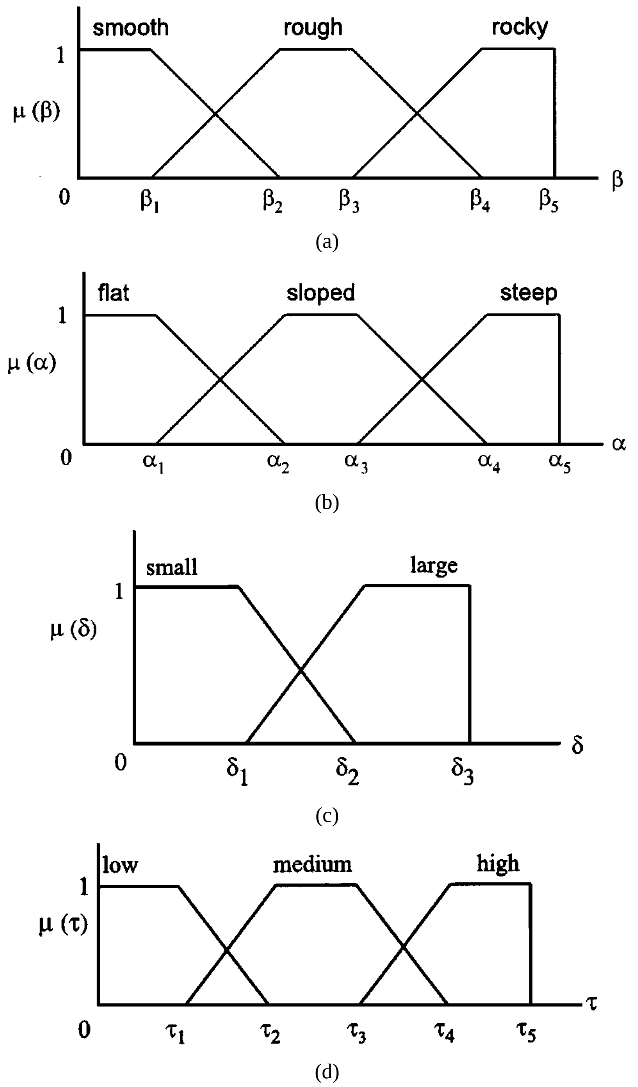


Fig. 1. (a) Membership functions for terrain roughness. (b) Membership functions for terrain slope. (c) Membership functions for terrain discontinuity. (d) Membership functions for traversability index.

gives the terrain slope value, whose magnitude is then converted into the three linguistic fuzzy sets {FLAT, SLOPED, STEEP}, with the membership functions shown in Fig. 1(b). The process of refining the membership functions by embedding human knowledge can also be applied in this instance.

An exception to the slope determination algorithm involves detection of terrain features such as cliffs, valleys, and ravines. For such features, the ground plane will have zero slope, and yet the terrain directly adjacent to the ground surface will have approximately a $\pm 90^\circ$ incline. For these cases, we determine the existence of a cliff/valley/ravine based on the separation distance between the two adjacent regions. We characterize this separation distance by the two linguistic fuzzy sets {SMALL, LARGE}, with the membership functions shown in Fig. 1(c).

Note that the definitions of the above classes of terrain characteristics depend on the wheel design and traction mechanism of the robot, which determine its hill climbing and rock climbing capabilities. This dependence is reflected in the selection of the membership functions used to represent the roughness, slope, and discontinuity characteristics as shown in Figs. 1(a)–1(c). For instance, robots with larger wheels can climb bigger rocks, and this fact can be reflected in definition of the membership functions for SMALL and LARGE fuzzy sets for rock size.

2) Terrain Traversability Index: The Fuzzy Rule-Based Traversability Index combines the three terrain quality parameters into a single indicator of ease of traversal of the terrain by the mobile robot. The Traversability Index τ is represented by the three linguistic fuzzy sets {LOW, MEDIUM, HIGH}, with the membership functions shown in Fig. 1(d). These indices correspond to terrains that are unsafe, risky, and safe for traversal, respectively. The Traversability Index τ is defined in terms of the terrain slope α, the terrain roughness β, and the terrain discontinuity δ by a set of simple intuitive fuzzy logic relations as follows:

1) IF α is FLAT AND β is SMOOTH AND δ is SMALL, THEN τ is HIGH.
2) IF α is FLAT AND β is ROUGH AND δ is SMALL, THEN τ is MEDIUM.
3) IF α is SLOPED AND β is SMOOTH AND δ is SMALL, THEN τ is MEDIUM.
4) IF α is SLOPED AND β is ROUGH AND δ is SMALL, THEN τ is LOW.
5) IF α is STEEP OR β is ROCKY OR δ is LARGE, THEN τ is LOW.

The last rule states that a terrain region with a STEEP slope, or a ROCKY roughness, or a LARGE discontinuity is unsafe for traversal, regardless of the values of the other two parameters. Note that multiple rules can be active at the same time and the fuzzy classes have overlaps; hence, the Traversability Index can have, for instance, both 0.5 MEDIUM and 0.5 HIGH membership values. This approach lends itself to a perception-based, linguistic definition of terrain traversability as used by a human observer, in contrast to a mathematical definition of traversability (as an analytical function of slope and roughness) used in existing methods. The multivalued nature of the proposed fuzzy logic representation of traversability offers significant robustness and tolerance to the large amount of uncertainty and imprecision inherent in sensing and perception of a natural terrain. This robustness is due to the fact that the output of a rule-based system does not depend on the *exact* values of the input variables. This allows each input variable to change over a range of values without affecting the system output.

B. Terrain-Based Navigation

The motion control variables of the mobile robot are the translational speed v and the rotational speed (or turn rate) ω, where $v = \sqrt{(dx/dt)^2 + (dy/dt)^2}$, $\omega = (d\theta/dt)$, and x, y and θ are the position coordinates of the robot center and the robot orientation in a user-defined coordinate frame of reference, respectively. The robot speed v is represented by the three linguistic fuzzy sets {STOP, SLOW, FAST}, with the membership functions shown in Fig. 2(a). Similarly, the robot turn rate ω is represented by the seven linguistic fuzzy sets {LARGE-NEG, MEDIUM-NEG, SMALL-NEG, ZERO, SMALL-POS, MEDIUM-POS, LARGE-POS}, with the membership functions shown in Fig. 2(b), where POSitive

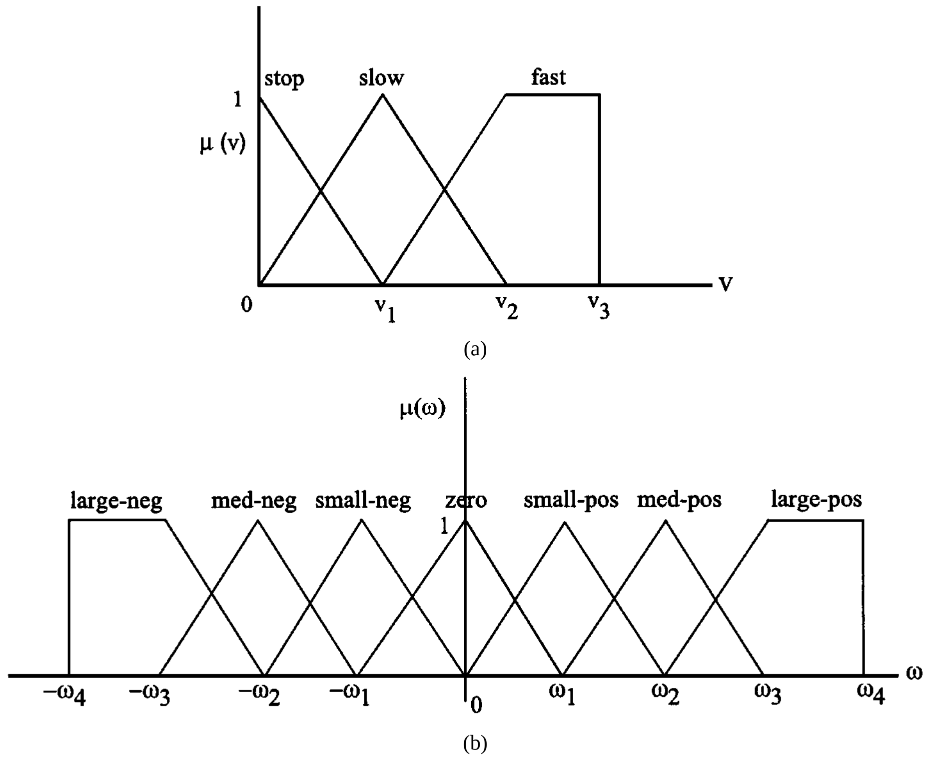


Fig. 2. (a) Membership functions for speed. (b) Membership functions for turn rate.

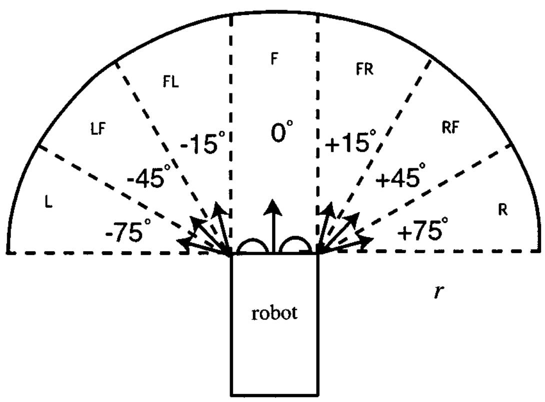


Fig. 3. Decomposition of terrain into seven sectors.

and NEGative turn the robot to right and left directions, respectively. These turn rates are used to change the robot heading and place the robot in an appropriate terrain sector.

In this section, the Traversability Index is used to develop simple rules for determination of the robot turn rate and speed while moving on a natural terrain. It is assumed that the robot can only move in the forward direction (i.e., reverse motion is not allowed). As shown in Fig. 3, the terrain available for robot traversal is divided up into a rectangular front sector and six 30° circular side sectors with radius r, where r is the user-defined *regional perception range* of the robot, i.e., the distance at which we wish the robot to react to the regional terrain characteristics[2]. These sectors are labeled from right to left as R (right), RF (right-front), FR (front-right), F (front), FL (front-left), LF (left-front), and L (left), and have the central angular values of $+75^\circ$, $+45^\circ$, $+15^\circ$, 0°, -15°, -45°, and -75° relative to the front direction, respectively. These seven sectors correspond to the seven classes of turn rate discussed earlier. In other words, LARGE-POS turns the robot to face the RIGHT sector, MEDIUM-POS to the RIGHT-FRONT sector, SMALL-POS to the FRONT-RIGHT sector, ZERO to the FRONT sector, and likewise for negative turn rates. The Traversability Indices for the above seven regions, τ_r, τ_{rf}, τ_{fr}, τ_f, τ_{fl}, τ_{lf}, and τ_l, are inferred from the perceived values of the terrain slope, roughness, and discontinuity of each region obtained by the vision system on board the robot.

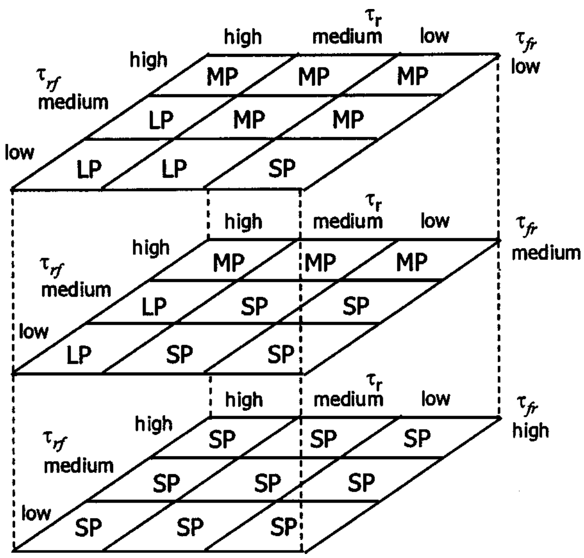
We shall now discuss the fuzzy logic rules for determination of the robot turn rate and speed, based on the terrain-traversability data. Note that if higher resolution is needed, the terrain in front of the robot can be decomposed into a larger number of smaller sectors, and similar navigation rules can be developed.

1) Turn Rules: We develop a two-step procedure for determining the turn rate. In the first step, we find the *most* traversable sector in the right and left regions *independently*, with preference (bias) toward the front direction. In the second step, we determine the best sector among the preferred-right, preferred-left, and front sectors.

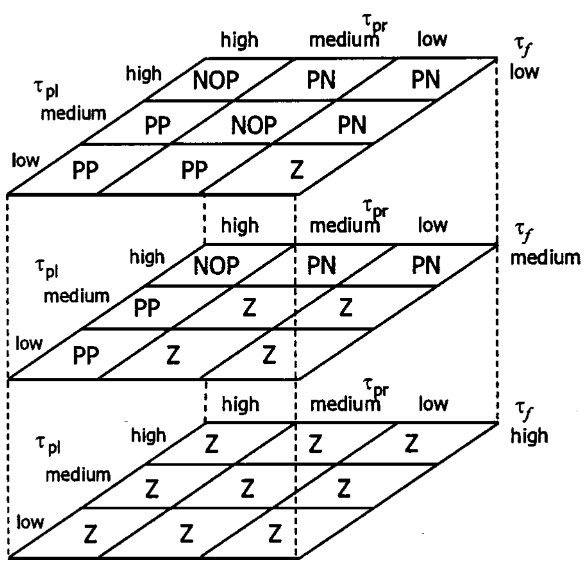
The turn rules for the first step are summarized in Table I(a) (for the right sector) to find the preferred-right (PR) sector with Fuzzy Traversability Index τ_{pr}, where LP is LARGE-POS, MP is MEDIUM-POS and SP is SMALL-POS. For instance, the (1, 1) element of the top layer in Table I(a) can be written out as IF τ_{fr} is LOW AND τ_r is HIGH AND τ_{rf} is HIGH, THEN ω is MEDIUM-POS, and the entire bottom layer can be written out as IF τ_{fr} is HIGH, THEN ω is SMALL-POS. Observe that the rules have a tendency

[2]Note that the regional perception range is less than or equal to the sensing envelope of the on-board terrain sensors. The value of r determines the location of the regional terrain boundary or *horizon line* in [18].

TABLE I
(a) TURN RULES TO SELECT PREFERRED-RIGHT (PR) SECTOR
(b) TURN RULES FOR THE TRAVERSE-TERRAIN BEHAVIOR



(a)



(b)

(bias) to select the direction that is closest to the front direction, so that the robot does not make unnecessary rotations. A similar rule set can be produced for the left sectors by replacing r and P by l and N. The outputs of the first step are the preferred-positive (PP) and preferred-negative (PN) turn rates associated with the preferred-right and preferred-left sectors. The turn rules for the second step are shown in Table I(b), where Z stands for ZERO. These rules compare the preferred-right (PR), preferred-left (PL), and front (F) sectors, and select the most traversable sector among them. Observe that a turn maneuver is not initiated when either the front sector is the most traversable, or the preferred-right and preferred-left sectors have the same traversability indices as the front sector. Notice that in Table I(b), when the robot needs to turn, but the PR and PL sectors have the *same* traversability indices, then the recommended turn rate is NOP (negative-or-positive), where NOP $=$ OR (PN, PP). The membership function of NOP is the union of the membership functions of PN and PP. For instance, IF τ_f is LOW AND τ_{pl} is HIGH AND τ_{pr} is HIGH, THEN ω is NOP. The advantage of using NOP over choosing either negative or positive as the recommended turn rate is that it does not force the robot to choose between left and right directions arbitrarily at this stage, keeping both options equally open for selection later. The final selection will be made when NOP is integrated with turn recommendations from other behaviors.

2) Move Rules: The translational speed of the robot is determined by the quality of the terrain sector facing the robot, that is, τ_f. This determination is formulated as a set of three simple fuzzy logic rules for speed of traverse as follows.

1) IF τ_f is LOW, THEN v is STOP.
2) IF τ_f is MEDIUM, THEN v is SLOW.
3) IF τ_f is HIGH, THEN v is FAST.

Note that when the robot turns to face a more traversable terrain sector, the front traversability index τ_f is updated automatically based on the new terrain quality information.

V. LOCAL AVOID-OBSTACLE BEHAVIOR

In a manner similar to the traverse-terrain behavior, it is assumed that there are seven groups of proximity sensors mounted on the robot facing the seven sectors of right, right-front, front-right, front, front-left, left-front and left. These sensors report the distances between the robot and the *closest* obstacle in each of the seven sectors, namely $\{d_r, d_{rf}, d_{fr}, d_f, d_{fl}, d_{lf}, d_l\}$. Each obstacle distance is represented by the three linguistic fuzzy sets {VERY-CLOSE, CLOSE, DISTANT}. The collision avoidance navigation rules are discussed below.

A. Turn Rules

The fuzzy logic turn rule sets are similar to those described in Section IV-B.1, with τ replaced by d and (low, medium, high) replaced by (very-close, close, distant) in Table I(a)–I(b). Note that when d_f is DISTANT, i.e., the front sector of the robot is clear of obstacles, the robot will not collide with any obstacles and no corrective action needs to be taken. Again, as in Section IV-B.1, when preferred-right and preferred-left sectors are equally obstacle free and better than the front sector, this behavior will recommend NOP (negative-or-positive) for the turn rate.

B. Move Rules

The robot speed is based on the closest obstacle distance in the front sector facing the robot, that is, d_f. The speed rules are as follows.

1) IF d_f is VERY-CLOSE, THEN v is STOP.
2) IF d_f is CLOSE, THEN v is SLOW.
3) IF d_f is DISTANT, THEN v is FAST.

Again, note that when the robot turns to face a more obstacle-free sector, the front obstacle distance d_f is updated automatically.

VI. GLOBAL SEEK-GOAL BEHAVIOR

In this section, we present a set of fuzzy logic navigation rules that drive the robot from a known initial position to a user-specified goal position, regardless of the terrain quality or obstacle presence. In these rules, the robot initially performs an in-place rotation toward the goal to nullify the heading error. Once the robot is aligned with the goal direction, it then proceeds toward the goal position on a straight path. A similar rule set can also be formulated for robots that are unable to perform in-place rotation. For this class of robots, the robot is commanded to move slowly toward the goal while turning simultaneously to face the goal position.

A. Turn Rules

The rules for the robot rotational motion are as follows:

1) IF ϕ is GOAL FAR-LEFT, THEN ω is LARGE-NEG;
2) IF ϕ is GOAL MEDIUM-LEFT, THEN ω is MEDIUM-NEG;
3) IF ϕ is GOAL LEFT, THEN ω is SMALL-NEG;
4) IF ϕ is GOAL HEAD-ON, THEN ω is ZERO;
5) IF ϕ is GOAL RIGHT, THEN ω is SMALL-POS;
6) IF ϕ is GOAL MEDIUM-RIGHT, THEN ω is MEDIUM-POS;
7) IF ϕ is GOAL FAR-RIGHT, THEN ω is LARGE-POS;

where ϕ is the heading error (goal bearing) and is represented by the seven linguistic fuzzy sets {GOAL FAR-LEFT, GOAL MEDIUM-LEFT, GOAL LEFT, GOAL HEAD-ON, GOAL RIGHT, GOAL MEDIUM-RIGHT, GOAL FAR-RIGHT}.

B. Move Rules

The following rules are used for the robot translational motion:

1) IF d is VERY-NEAR OR ϕ is NOT GOAL HEAD-ON, THEN v is STOP;
2) IF d is NEAR AND ϕ is GOAL HEAD-ON, THEN v is SLOW;

where d is the position error (goal distance) and is represented by the two linguistic fuzzy sets {VERY-NEAR, NEAR} when the robot is close to the goal. The above rules slow down the robot motion as it gets close to the goal. The first rule also keeps the robot stationary while it is correcting its heading. Observe that when the robot is far from the goal, its speed is dictated by the local obstacle distance and the regional terrain quality, and is generated by the move rules in the local avoid-obstacle and regional traverse-terrain behaviors. In this case, the seek-goal behavior does not contribute to the robot speed.

VII. Integration of Multiple Behaviors

The regional traverse-terrain behavior, the local avoid-obstacle behavior and the global seek-goal behavior described in Sections IV–VI compete for control of the mobile robot by issuing *independent* motion recommendations for the *same* vehicle. These different recommendations must therefore be reconciled and fused in order to generate the final motion command. To resolve conflict among behaviors, a strategy must be constructed to determine which behavior or combination of behaviors must be active at any given time. It is at this point that most strategies diverge in the type of process used for conflict resolution. Some of the earlier strategies, e.g., [20], are based on Brooks' subsumption architecture [21] using a switching type of behavior arbitration. This method employs a prioritization scheme wherein the recommendation of only one behavior with the highest priority is selected, while recommendations of the remaining competing behaviors with lower priorities are ignored. Unfortunately, this type of approach leads to inefficient performance in certain situations. For example, a robot encounters an obstacle situated directly in front of its current path and the avoid-obstacle behavior is selected. The robot then decides to turn left to avoid the obstacle. However, the goal is located to the right, but since the avoid-obstacle behavior is not privy to this information, its decision hampers the progress of the seek-goal behavior. Other techniques, e.g., [22], focus on combining the output of each behavior using predetermined weighting factors. This leads to direct conflicts in execution when multiple behaviors give contrary commands. For example, the avoid-obstacle behavior commands the robot to turn left to avoid collision with a forward obstacle, while the seek-goal behavior commands the robot to turn right in the direction of the goal. Combining each behavior's output can result in a command directing the robot to move forward, which will cause the robot to eventually collide with the obstacle. To deal with these limitations, other strategies have employed fusion methodologies in which each behavior is allowed to affect the final output based on the situational context [4], [23], [24]. Saffiotti [4] focuses on using the process of context-dependent blending (CDB) in which the current situation is used to decide between behaviors using fuzzy logic. For example, the outputs from the avoid-obstacle and seek-goal behaviors are combined with equal weights until a situation occurs in which priority must be given to one behavior. Such a situation will occur when an obstacle is very close and, to avoid immediate collision, obstacle avoidance becomes the main concern. Independently, Tunstel *et al.* [23] develop an approach similar to context-dependent blending, in which an adaptive hierarchy of multiple fuzzy behaviors are combined using the concept of degree-of-applicability (DOA). In this case, certain behaviors are allowed to influence the overall behavior as required by the current situation and goal. Rosenblatt [24] develops the distributed architecture for mobile navigation (DAMN), in which a centralized arbitration of votes provided by independent behaviors combines into a unified output. This approach differs from the others in that behaviors can vote either for or against certain vehicle actions, rather than having to decide on one specific output. The DAMN arbiter selects the output command associated with the most votes.

The behavior fusion methodology we employ in this section is motivated by the approaches used by Saffioti [4] and Tunstel *et al.* [23]. Independent behaviors are executed in a concurrent fashion, and depending on the situational context, the outputs are blended together. Each behavior is assigned a weighting factor, and these factors are adjusted dynamically according to the weight rules. The weighting factors determine the degree of influence of each behavior on the final motion command. The weight rules combine elemental behaviors, not through fixed-priority arbitration, but rather through a generalization of dynamic gains that are determined based on consideration of the current status of the robot. The weight rules continuously update the behavior weighting factors during robot motion based on the prevailing conditions.

A. Rules for Behavior Weights

The weighting factors t^w, a^w, and s^w represent the strengths by which the traverse-terrain, avoid-obstacle and seek-goal recommendations are taken into account to compute the final motion commands $\bar{v}$ and $\bar{\omega}$. These weights are represented by the three linguistic fuzzy sets {LOW, NOMINAL, HIGH}. Two sets of weight rules for two behaviors are now presented.

The traverse-terrain weight rules are as follows.

1) IF τ_f is LOW, THEN t^w is HIGH.
2) IF τ_f is MEDIUM, THEN t^w is NOMINAL.
3) IF τ_f is HIGH, THEN t^w is LOW.

The avoid-obstacle weight rules are as follows.

1) IF d_f is VERY-CLOSE, THEN a^w is HIGH;
2) IF d_f is CLOSE, THEN a^w is NOMINAL;
3) IF d_f is DISTANT, THEN a^w is LOW;

where $_f$ denotes the *front sector*, i.e., the terrain sector facing the current robot heading. Finally, the seek-goal weight s^w is set to NOMINAL at all times. These weight rules essentially adjust the traverse-terrain and avoid-obstacle weights relative to the seek-goal weight in response to the prevailing conditions. Specifically, in critical conditions when the robot is facing an unsafe terrain segment or a nearby obstacle, the traverse-terrain or avoid-obstacle weighting factors are increased significantly to avoid the impending hazard, at the expense of deviating from the nominal path to the goal. Conversely, when the robot faces a safe obstacle-free terrain, the seek-goal behavior dominates and drives the robot toward the goal. Observe that the weight rules for each behavior are independent of the other behaviors. Furthermore, the above weight rules are complete and exhaustively partition the entire space of possibilities.

Note that the fuzzy logic navigation and weight rules developed in this paper can be applied to any mobile robot, regardless of robot characteristics such as wheel size, clearance, and so on. These characteristics are reflected only in the definition of the membership functions used in the fuzzy rules.

B. Behavior Integration Method

In our behavior-based navigation strategy, the three navigation rule sets recommend independent motion commands for the mobile robot, in the form of truncated membership functions that represent the output (v, ω) fuzzy sets. The truncation levels of the output fuzzy sets are determined by the activation levels of the input fuzzy sets of the rules that are fired [25]. At each control cycle, the weight rules are used to calculate the three crisp (nonfuzzy) weighting factors t^w, a^w, and s^w using the Center-of-Gravity (Centroid) defuzzification method [25]. The fuzzy recommendations from the traverse-terrain, avoid-obstacle, and seek-goal behaviors are then weighted by the corresponding crisp gains t^w, a^w, and s^w, respectively, prior to defuzzification, as shown in Fig. 4. The final motion commands are computed using the Centroid defuzzification method as

$$\bar{v} = \frac{s^w \Sigma v_p^s A_p^s + t^w \Sigma v_p^t A_p^t + a^w \Sigma v_p^a A_p^a}{s^w \Sigma A_p^s + t^w \Sigma A_p^t + a^w \Sigma A_p^a} \quad (3)$$

$$\bar{\omega} = \frac{s^w \Sigma \omega_p^s B_p^s + t^w \Sigma \omega_p^t B_p^t + a^w \Sigma \omega_p^a B_p^a}{s^w \Sigma B_p^s + t^w \Sigma B_p^t + a^w \Sigma B_p^a}. \quad (4)$$

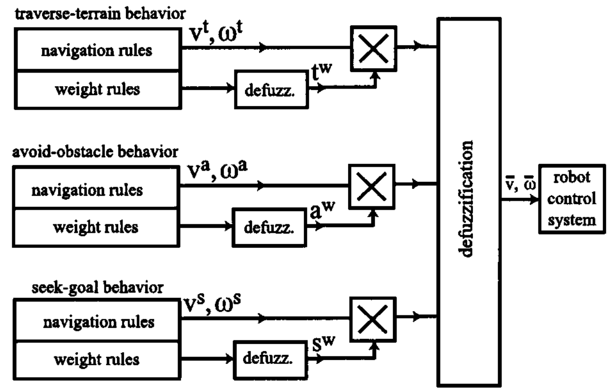


Fig. 4. Behavior integration method.

In the above equations, v_p and A_p are the peak membership value and the area under the truncated membership function for the velocity fuzzy sets, while ω_p and B_p are the corresponding values for the turn rate fuzzy sets. Note that in (3) and (4), the *relative* values of the weighting factors are important, and not their absolute values, i.e., if all the weights are equal, they will be cancelled out in (3) and (4).

In certain situations, the final output fuzzy set for ω has an almost symmetrical shape about the zero axis, e.g., the right and left turn recommendations have almost equal areas and the front direction is not recommended. In such situations, direct application of the standard Centroid defuzzification method can produce an undesirable motion recommendation, in which the robot is commanded in the front direction that may cause collision with a local obstacle or entry into an impassable terrain segment. To overcome this problem, in these situations we apply the Center-of-Largest-Area (CLA) defuzzification method [26], in which the output fuzzy set is first partitioned into two or more disjoint fuzzy subsets, and the subset with the largest area is then selected and defuzzified using the standard Centroid method[3]. This method resolves the indeterminate situation faced by the Centroid method and selects either the right or the left direction that steers the robot away from the front local obstacle or impassable segment.

Finally, when the goal is located within an unsafe sector (low traversability region), the robot motion is halted for safety reasons by using crisp (nonfuzzy) rules to set $\bar{v}$ and $\bar{\omega}$ to zero. Otherwise, when the robot reaches within a small user-specified distance of the goal, $\bar{v}$ and $\bar{\omega}$ are forced to zero by crisp rules and the robot comes to a halt.

VIII. Summary of Key Attributes and Comparison With Existing Methods

The key attributes of the proposed navigation approach are derived from the combined strengths of both fuzzy rule-based

[3]If the disjoint right and left subsets have exactly equal areas, then we choose either RIGHT or LEFT arbitrarily at this final stage as the "preferred" turn direction. Note that in this case, the selection of a preferred direction is essential at the final stage to avoid moving straight into the local obstacle or the impassable terrain segment. Observe that the selection of the preferred direction is deferred until the final stage.

systems and behavior-based navigation architectures. These attributes include:

1) *Linguistic Representation*: The navigation logic uses linguistic terms from a common natural language. This feature allows the navigation logic to employ a perception-based formulation. The proposed approach has the ability to interpret the navigation rules expressed in a natural language. This provides the capability to capture human common sense and intuitive reasoning, decision making, and other aspects of human cognition. This attribute can be used to model the human driving expertise.
2) *Uncertainty Management*: The foundation of fuzzy logic is representation of, and reasoning with, imprecise information. Fuzzy logic provides a systematic framework for dealing with imprecise and uncertain information. The input variables in a fuzzy conditional statement may vary over ranges of values without affecting the value of the output variable. Thus errors due to sensor noise and visual processing are effectively handled by the navigation system.
3) *Simplicity*: A distinct feature of the proposed approach is its simplicity. Each behavior in the navigation system is implemented by a small number of simple fuzzy logic rules with a few inputs and outputs. The knowledge base of each behavior is easy to comprehend, because it is captured in linguistic form by simple intuitive rule statements.
4) *Extensibility*: The behavior-based approach to robot navigation has a modular structure. The decoupled nature of the behavior-based system significantly reduces the number of rules needed for robot navigation. This structure also makes it easy to add new modules that represent additional behaviors to the system. This design makes the navigation logic easily extensible.
5) *Computational Efficiency*: The fuzzy rule-based navigation algorithm is computationally fast and efficient. The computations involved are evaluation of simple expressions, such as (3) and (4) in Section VII-B. Furthermore, the navigation algorithm has low computer memory requirements. The high computational speed coupled with the low memory needs of the navigation algorithm make it a strong candidate for real-time implementation on mobile robots.

The navigation strategy proposed in this paper can be viewed as the next generation of the navigation logic used on the Sojourner rover that explored the Martian terrain in 1997. The Sojourner rover used a behavior-based navigation method with a few simple linguistic rules [27]. The proposed navigation strategy belongs to the large family of *Expert Systems* defined in the artificial intelligence (AI) literature [28]. These systems are capable of embedding the human expert's domain knowledge in the form of a set of linguistic rules which contain imprecise and uncertain terms. Since much of the information in an expert system's knowledge base is imprecise in nature, fuzzy logic is used to provide a framework for uncertainty management [29]. This alliance of expert systems and fuzzy logic forms a strong alternative to conventional analytical methods in many applications.

We shall now give a broad comparison of the proposed approach and the existing navigation methods, such as those reviewed in Section II. The behavior-based navigation approach proposed in this paper is fundamentally different from the existing analytical navigation methods. For performance comparison, we focus on two specific aspects that are representative of the navigation system. First, the common theme in most existing methods is that the terrain traversability is represented either as an analytical function of the terrain characteristics, or as a binary quantity depending on these characteristics. The proposed approach, however, is built on reasoning with perception-based information expressed in a natural language. As a specific example, consider the assessment of terrain roughness and traversability using existing methods and the proposed approach. In most existing methods, the terrain roughness is typically obtained mathematically as the residual of the least-squares plane fit to the terrain segment. This measure of roughness can lead to counterintuitive results for some terrains. For instance, given a flat smooth terrain with a few large rocks, we obtain a large residual that results in high roughness and low traversability. On the other hand, using the proposed approach, the terrain roughness is found from a set of intuitive linguistic rules given in Section IV-A.1 that are representative of human perceptual judgment. When applied to the same terrain segment described above, the rules produce an intuitive evaluation of roughness as ROUGH and terrain traversability as MEDIUM. Second, in existing methods for navigation, data uncertainty is often dealt with through probability-based methods. These methods are not fully capable of handling the pervasive fuzziness of information present in the knowledge base of the navigation system. Imprecision in sensory measurements, and uncertainty in data interpretation in the knowledge base, are mostly based on possibility rather than probability. Fuzzy logic-based methods, such as the proposed approach, have a built-in intrinsic framework that is designed to address approximate reasoning using uncertain information, where the uncertainty can be based both on possibility and probability [29].

IX. Field-Test Studies

The test and evaluation of the proposed navigation strategy was conducted in three phases: graphical simulations, laboratory tests, and field tests. In the first phase, a software package called the Robot Graphical Simulator was developed at JPL for two–dimensional visualization of the robot motion using the fuzzy rule-based navigation strategy [30]. The robot kinematics and the on-board sensors were modeled in the software. Extensive graphical simulations were carried out for test and evaluation in different terrain layouts, as well as for comparison with the Sojourner navigation system [30]. In the second phase, the navigation strategy was implemented on an enhanced Pioneer commercial robot (see below). A typical outdoor terrain consisting of flat regions, sloped surfaces and large rocks was set up in the laboratory. The rover navigation strategy was tested extensively in the indoor laboratory environment.

In the third phase, field tests using the Pioneer All-Terrain (AT) commercial mobile robot (rover) are conducted on rough

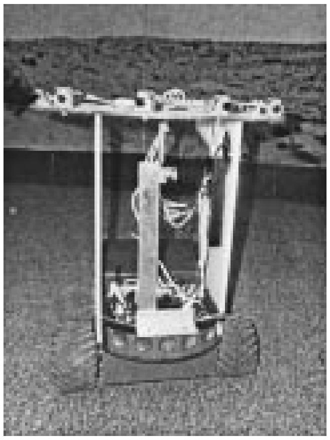


Fig. 5. Pioneer rover with enhancements.

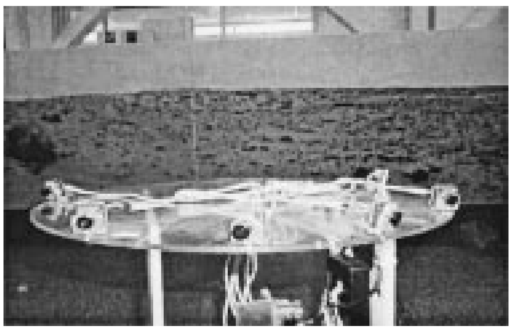


Fig. 6. Terrain sensor platform.

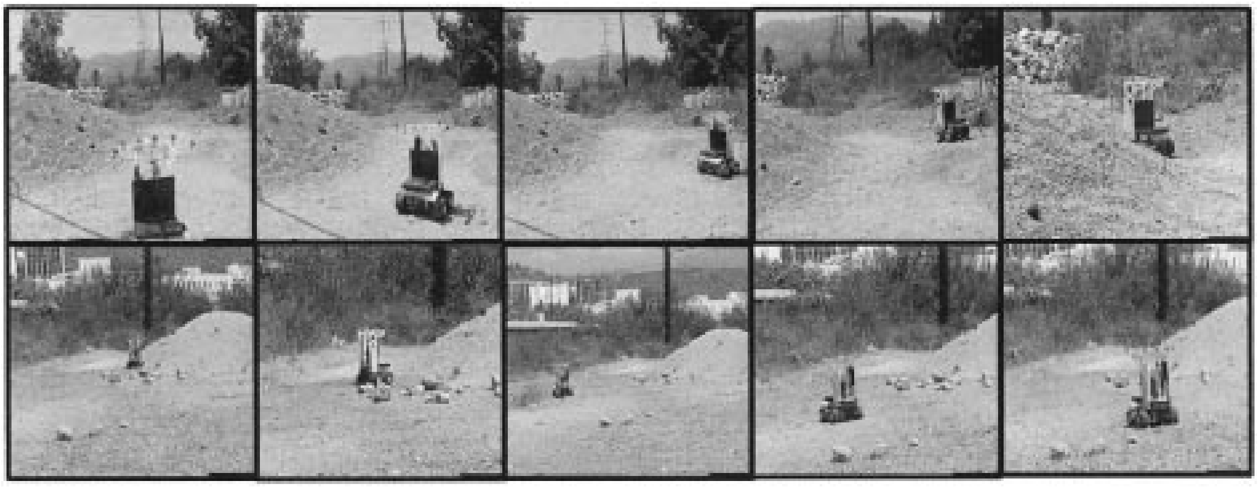
terrain in the arroyo (a dry river bed) outside JPL to test the reasoning and decision-making capabilities provided by the fuzzy logic behavior-based navigation strategy described in Sections IV–VII. Fig. 5 shows the Pioneer rover augmented with additional on-board processing capability, eight-input image multiplexer and six video cameras. Fig. 6 shows the physical layout of the camera platform used specifically to provide terrain imagery data. The six cameras are placed such that the lens centers are 740 mm above the ground, the optical axis of each camera is tilted down by 8°, the stereo baseline length is set to 500 mm, and the intersecting origin of all cameras is centered above the rover wheels. Each pair of cameras views a 60° wedge of the terrain located to the front, right, and left of the rover. In other words, the cameras partition the terrain into three 60° circular sectors with a sensing radius of about eight meters[4]. The traversability indices of the front, right, and left sectors are inferred in real time from the terrain characteristics extracted from the camera images. The regional perception range r for the traverse-terrain behavior is set to eight meters, i.e., the robot reacts to terrain characteristics up to eight meters away. The robot stops every eight meters (measured on a straight line from previous stop) at a waypoint for re-evaluation of the new encountered terrain. There are seven sonars mounted on the rover base for obstacle detection. The outputs of these sonars are grouped together to produce the closest obstacle distance in the front, right, and left sectors. The rover is able to determine its current location and heading, relative to a given start configuration, by dead reckoning using its internal wheel-encoder information. The processing power on board the rover consists of a 333 MHz Pentium II processor housed in a chassis mounted at the rear of the rover. We have chosen to use the Linux operating system, but have also tested the system using a laptop computer running Windows. Resident on the computer are the image processing algorithms and the fuzzy logic computation engine used to calculate the translational and rotational speed commands issued to control the wheel motors. Using this mobile platform, field tests are performed outdoors in natural terrain. Fig. 7 shows the terrain environment with the rover start position located at the bottom center of the image. Three field tests are conducted to evaluate the navigation capabilities of the rover.

[4]This is a coarser resolution than the method described in Section IV, but is adequate for our field testing.

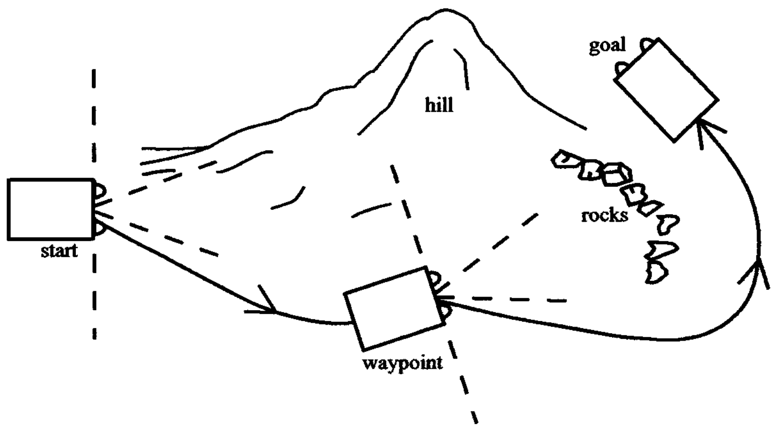
Fig. 7. Natural terrain environment.

A. Field Test One

In the first field test, the three navigation behaviors, traverse-terrain, avoid-obstacle, and seek-goal, are utilized by the rover to navigate from a start position to a user-specified goal position, while traversing the safest terrain and avoiding encountered obstacles. The goal position is chosen approximately 20 meters in front of the rover, measured on a straight line. Directly in-between the start and goal positions are two regions having low traversability. One region contains a highly sloped hill, and the other contains a large cluster of rocks, as seen in Fig. 7. The rover first begins by analyzing the traversability of the three partitioned 60° sectors (left, front, right) of the terrain located in front of it. The front and left sectors (which contain the large sloped hill) are found to have low traversability. The rover therefore turns toward the right sector, which is found to be highly traversable, and proceeds to enter the safe region. Once in the safe region, the rover travels toward a waypoint eight meters from the start position (measured on a straight line), while ensuring that it is still physically located in the highly traversable sector. After reaching the waypoint, the rover stops, turns toward the goal and re-analyzes the traversability of the new terrain ahead of it. This time, the front sector is found to have low traversability due to the large cluster of rocks located in this area. The left region is found to have low traversability due to the large sloped hill, and the right region is once again found to have high traversability. The rover thus turns to the right again and proceeds into the safe region. At this stage, the terrain in front of the rover is highly traversable and obstacle free. Therefore, the weights on the traverse-terrain and avoid-obstacle recommendations are reduced automatically, and the seek-goal behavior becomes dom-



(a)



(b)

Fig. 8. (a) Rover path using fuzzy logic navigation rules. Top-left image shows rover start position and bottom-right image indicates goal achievement. Image sequence proceeds to the right and down. (b) Sketch of test site and approximate rover path.

inant. At this point, the rover heads directly toward the goal on a straight path. Fig. 8(a) shows the path traversed by the rover from its original start position until it has autonomously reached the specified goal position, using its on-board fuzzy logic navigation and weight rules. Fig. 8(b) shows a free-hand sketch of the test site features and the approximate path traversed by the rover in this field test.

B. Field Test Two

In the second field test, the influence of the traverse-terrain behavior on the rover navigation logic is demonstrated. In this setup, the goal position is chosen approximately 10 meters directly in front of the rover. In addition, a large cluster of rocks is located directly between the rover start position and the specified goal position. For the first test, the rover is commanded to navigate to the specified goal position while the traverse-terrain behavior is disabled, i.e., the recommendations of the traverse-terrain behavior are totally ignored by presetting the traverse weight to zero. As the rover navigates toward the goal, it enters into the cluster of rocks. At this point, the rover slows down and creeps its way into the center of the cluster. Eventually, the rover halts when its sonars detect rock obstacles located on all three sides (front, left, right). As shown in Fig. 9(a), the rover easily gets trapped in the cluster of rocks. For the second test, the traverse-terrain behavior is enabled, and the rover is shown to successfully reach the goal position (Fig. 9(b)). In this test, the front sector is found to have low traversability due to the rock cluster, and thus, the traverse-terrain behavior commands the rover to circumnavigate the cluster of rocks. Fig. 9(c) shows the approximate rover paths in both cases. This test demonstrates that the traverse-terrain behavior can effectively analyze and incorporate the terrain information directly into the navigation logic and enhance mission success by preventing entry and entrapment of the rover in the rock cluster.

C. Field Test Three

In the third field test, the influence of surface discontinuity on the fuzzy logic navigation is analyzed. In this setup, the rover is commanded to approach a goal position located four meters directly in front of the rover. In addition, a cliff edge is also located directly in front of the rover less than four meters away. The on-board navigation system first begins by analyzing the traversability data of the left, front, and right regions of the terrain located in front of the rover. The front and left sectors both contain images of the cliff, and thus, are found to have low traversability due to detection of a large surface disconti-

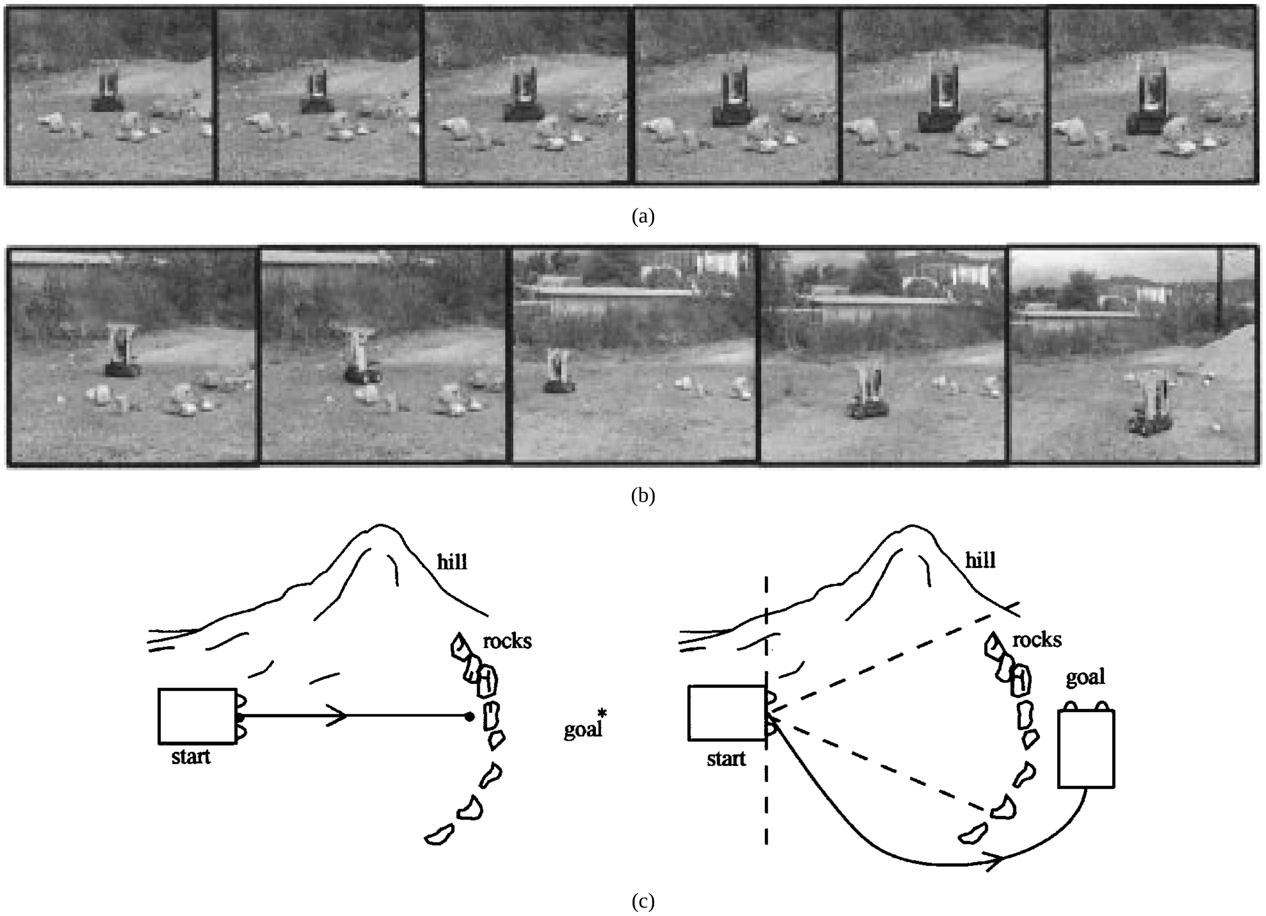


Fig. 9. (a) Entrapment without traverse-terrain behavior. (b) Circumnavigation with traverse-terrain behavior. (c) Approximate rover paths.

nuity. The right sector is found to have medium traversability, and therefore the rover turns right and proceeds to enter the safer region upon which the rover motion is halted since the goal is unattainable. Thus, the rover attempts to navigate toward the goal but successfully turns away to avoid the cliff region. This behavior is shown in Fig. 10(a) and in the free-hand sketch of Fig. 10(b).

D. Performance Metric

The performance metric used for the evaluation of our field tests parallels the one used by JPL for the Sojourner Mars rover [27]. This metric evaluates the probability that the rover will attain the designated goal for a given set of test runs over a given set of test scenarios. Based on this metric, we evaluated 10 different test scenarios, with the rover operating on each test scenario for five independent runs. A run was declared successful when the rover's position estimate implied that the goal was attained. The rover reached the goal in 80% of the runs for each field test, except in field test three where the designated goal was chosen to be unattainable. The quantitative results used in the evaluation of the field tests are listed as follows:

1) average rover speed: 20 cm/s;
2) average distance traveled: 35 m;
3) average travel time: 3 min;
4) runs attempted: five runs each of ten different scenarios;
5) success rate: 80%.

A run is declared unsuccessful when the distance between the designated goal position and the rover's final position exceeds one meter, which is about 3% of total traversal distance on average. After analysis, we concluded that there were three main causes for the unsuccessful runs. One cause was the skid-steering mechanism of the Pioneer rover, in which the dead reckoning used for estimating the rover location and heading tends to give inaccurate information. This inaccuracy is caused by wheel slippage and sinkage and can be excessive for long rover traversals. The dead reckoning error was more noticeable in the rover heading estimation, leading sometimes to incorrect rover heading after about 20 m traversal. Another cause was the analysis of traversability in lighting conditions that result in excessive shadows [18]. In these cases, the traversability results were inaccurate and, in some situations, all regions were considered unsafe, thus halting the rover before it could attain the goal position. The last cause of unsuccessful runs was sonar errors which occurred when detecting rocks with sharp corners. In these cases, the sonar was unable to detect the obstacle, due to the nature of sonar operation, and the rover would head straight toward the obstacle.

Finally, as shown in the test images, the traverse-terrain behavior chooses the safest traversable region for the rover in all test cases. The field test studies thus demonstrate the capability of the terrain assessment and fuzzy logic navigation algorithms for enabling safe traversal of the rover on a challenging terrain.

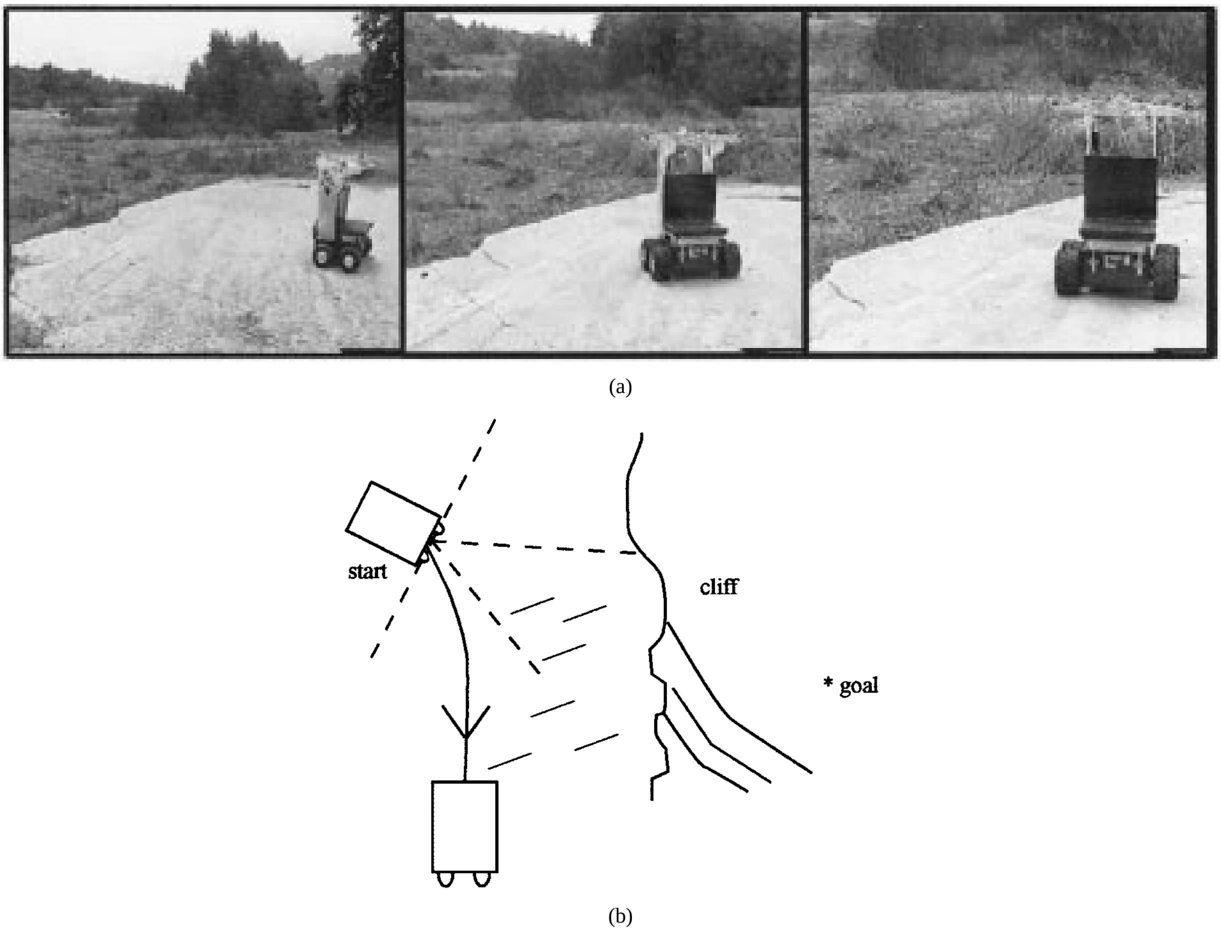


Fig. 10. (a) Rover path with large surface discontinuity. (b) Approximate rover path.

Notice that the membership functions of the fuzzy sets used in the navigation system are chosen by trial-and-error based on the physical capabilities of the Pioneer AT rover.

X. Conclusions

The proposed behavior-based robot navigation strategy using fuzzy logic rules has major advantages over existing analytical methods. First, the fuzzy logic rules that govern the robot motion are simple and easily understandable, and can emulate the human driver's perception, knowledge, and experience. Second, the tolerance of fuzzy logic of imprecision and uncertainty in sensory data is particularly appealing for outdoor navigation, because of the inherent inaccuracy in measuring and interpreting the terrain quality data, such as slope, roughness, and discontinuity. And third, the behavior-based strategy has a modular structure that can be extended very easily to incorporate new behaviors, whereas this requires complete reformulation for analytical methods. Multiple fuzzy navigation behaviors are combined into a unified strategy, together with smooth interpolation between the behaviors to avoid abrupt and discontinuous transitions.

The addition of the on-board terrain sensing and traversability analysis, coupled with the traverse-terrain behavior that takes advantage of this information, are significant and novel contributions of this paper. These capabilities allow the navigation system to take preventive measures by looking ahead, preventing the robot from entry and entrapment in rock clusters and other impassable regions, and instead guide the robot to circumnavigate these regions. However, it must be pointed out that the perception range of the traverse-terrain behavior is limited to the regional terrain sensed by the on-board cameras, and does not include the longer range global-scale terrain features. As such, this behavior cannot prevent the robot from getting trapped in a large cul-de-sac or box canyon. These situations, however, can be avoided using a global map-based path planner that generates an optimally safe path clear of global hazards, which is then passed on to the sensor-based navigation system. The new regional traverse-terrain behavior introduced in this paper complements the local avoid-obstacle and global seek-goal behaviors commonly used in behavior-based navigation systems. The field test studies reported in this paper demonstrate that the mobile robot possesses intelligent decision-making capabilities that are brought to bear in negotiating hazardous terrain conditions during the robot motion.

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