Approximate reasoning for safety and survivability of planetary rovers

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Abstract

Operational safety and health monitoring are critical matters for autonomous planetary rovers operating on remote and challenging terrain. This paper describes rover safety issues and presents an approximate reasoning approach to maintaining vehicle safety in a navigational context. The proposed rover safety module is composed of two distinct behaviors: safe attitude (pitch and roll) management and safe traction management. Fuzzy logic implementations of these behaviors on outdoor terrain is presented. Sensing of vehicle safety coupled with visual neural network-based perception of terrain quality are used to infer safe speeds during rover traversal. In addition, approximate reasoning for self-regulation of internal operating conditions is briefly discussed. The core theoretical foundations of the applied soft computing techniques is presented and supported by descriptions of field tests and laboratory experimental results. For autonomous rovers, the approach provides intrinsic safety cognizance and a capacity for reactive mitigation of navigation risks.

Key words: approximate reasoning, fuzzy inference systems, robotics, planetary rovers, neural networks, vision-based control, off-road mobility

1 Introduction

To explore the surface of planet Mars, NASA uses mobile robots that are designed to rove across the surface in search of clues and evidence about the history of the planet. These planetary rovers have mobility characteristics that are sufficient for traversing rough and rugged terrain containing hazards such as extreme slopes, sand or dust-covered pits, ditches, cliffs and otherwise impassable surfaces. To consistently avoid these mobility hazards and when necessary, negotiate challenging terrain, they must continuously assess the safety of traversal and take autonomous reactive measures to maintain vehicle safety and nominal operation.

Many existing autonomous mobility systems focus on *strategic* navigation goals and disregard intrinsic vehicle safety and health monitoring [1,2]. These issues are often treated as secondary research concerns relative to the more popular problems of motion control, navigation, mapping, and planning. Vehicle health and safety are primary concerns, however, in field mobile robot research for remote applications. In rover systems that do incorporate some level of health monitoring [3,4], the common practice is to consider basic monitoring of individual hardware components for proper operation, without incorporating explicit autonomous reaction or counter-action by the rover. Few field mobile robot systems have been reported in the literature that feature efficient implementation of active countermeasures for both vehicle health *and* safety in a comprehensive fashion. Ultimately, such comprehensive systems are desired to increase rover survivability. Before this can be achieved a number of challenges must be addressed.

Complete observability of all relevant states, events, and terrain features that affect rover safety is rare in practice. New strategies must be considered that are effective in situations of limited observability and uncertain information. In addition, space flight missions require the use of space flight-qualified or radiation-hardened electronics that will survive and operate in the harsh temperature and radiation extremes of outer space and at planets with thin atmospheres. These constraints on rover computing hardware cannot be met by most commercially available electronics. The computers that are available for space systems are typically limited in speed, processing power, and memory capacity relative to today's generic desktop computers. Hence, the solution space is restricted to efficient and compact embedded applications. This situation intensifies the need for innovative rover computing solutions. New strategies are needed that enable the necessary on-board autonomy in compliance with the practical limitations and constraints.

In the face of these challenges, we have concentrated on developing new strategies for using approximate reasoning to implement intuitively simple solutions to safe mobility. The solutions incorporate fuzzy logic techniques that enable intelligent control with modest computational overhead. The utility of fuzzy logic techniques has been proven for solving aspects of the popular mobility problems [2]. We show that the same underlying fuzzy logic and control techniques used for strategic navigation can also be applied to provide capabilities for robot health monitoring and safety. Approximate reasoning is adopted to address this problem due to the necessity to process uncertain environmental information and to compensate for sensing and perception limitations of the rover. The tolerance of fuzzy logic to imprecision and uncertainties in sensory data is particularly appealing for outdoor rover navigation because of the inevitable inaccuracies in measuring physical quantities using low-power sensors, and interpreting sensory data using modest processing power. At the control level, interpolation properties of fuzzy sets and logical inference are exploited to realize smooth reactions to unsafe vehicle configurations. In addition to efficiency in computing and control robustness, our strategy is motivated by a desire to emulate human judgment and reasoning as derived from off-road driving heuristics [5]. Fuzzy logic is a convenient choice for endowing a computing system with human-like algorithmic reasoning capabilities.

This paper describes hybrid soft computing solutions aimed at providing built-in safety and survivability behaviors for planetary rovers. Fuzzy logic techniques and neural networks are employed to construct intelligent safety behaviors that enable safe and reliable autonomous navigation in remote challenging terrain. We provide descriptions of these techniques, as well as the visual perception algorithms that complement the approximate reasoning approach. The following sections provide a brief overview of the navigation system supported by the safety module, and describe relevant rover safety and health issues. Next, a fuzzy logic approach to vehicle safety reasoning is presented that provides intrinsic safety cognizance and a capacity for reactive mitigation of navigation risks. Field test and experimental results are also presented.

2 Overview of navigation system

Rough and rugged outdoor terrain can be difficult to traverse even for a human driver of an off-road vehicle. The difficulty of the problem increases by orders of magnitude for an autonomous rover. Nonetheless, human driver performance is a worthy goal to strive for in the design of a rover navigation system. In part, we have sought to develop fuzzy inference systems that emulate the judgment and reasoning of a cautious human driver. The resulting safe navigation system is comprised of the various modules and components shown in Fig. 1. With the exception of the low-level rover motion control system, each component is implemented using soft computing techniques – primarily fuzzy reasoning and control along with artificial neural networks, embedded within a behavior-based structure. The system consists primarily of modules dedicated to rover safety reasoning and strategic navigation control. These are accompanied by associated perception and actuation functionality. The strategic navigation module handles mission and goal-directed motion from place to place. The safety reasoning module, which is the focus of this paper, ensures vehicle survivability and operational health.

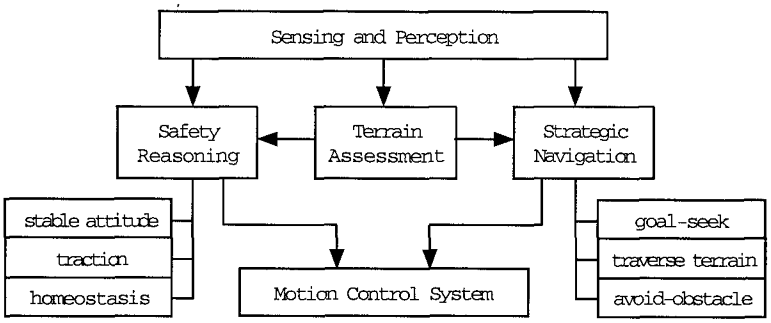


Fig. 1. Organization of navigation system.

We have adopted a fuzzy behavior-based approach [6] to implement knowledge-based reasoning and control components. For this work each safety component, or behavior, represents a mapping from perceptions to actions aimed at achieving a given desired objective. Safety behaviors are encoded as fuzzy rule-bases that perform mappings from different subsets of the available sensor suite to set-points for common actuators. If X and U are input and output universes of discourse of a safety behavior with a rule-base of size n, the fuzzy IF-THEN rule takes the following form

$$IF\ x\ is\ \tilde{C}_i\ THEN\ u\ is\ \tilde{A}_i \tag{1}$$

where x and u represent input and output fuzzy linguistic variables, respectively, and $\tilde{C}_i$ and $\tilde{A}_i$ ($i = 1, 2, \ldots, n$) are fuzzy subsets denoting linguistic values of x and u, which represent possible conditions and actions. In our case, the input x refers to sensory data; u refers to safe rover speed recommendations which serve as set-points for low-level classical PID motor controllers. Equation 1 will be used to emulate a typical rule that expresses the actions taken by a cautious human driver based on the prevailing vehicle and road conditions. Fuzzy safety behaviors are synthesized as a finite set of such rules. In the sequel, we discuss our intuitive approach to reasoning about rover safety, followed by implementation details of each safety behavior.

3 Approximate reasoning for rover safety

Approximate reasoning facilitates processing of uncertain environmental information acquired by sensors on the rover, and thus, compensation for sensing and perception limitations of the rover. As an early step toward providing basic elements necessary for comprehensive rover health and safety, we consider the chassis attitude and the terrain surface type as prominent factors that affect rover survivability. Available power and internal operating temperature are also important as health indicators. We shall first discuss the basic approximate reasoning used to self-regulate power and internal temperature,

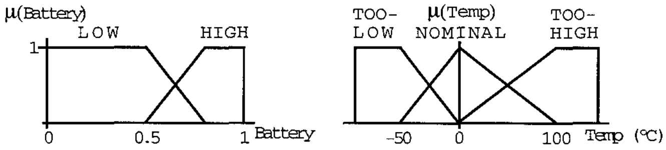


Fig. 2. Fuzzy sets for homeostasis-related measurements.

and later point out the main safety concerns related to chassis attitude and terrain surfaces.

The amount of power available to a rover system is perhaps the strongest indicator of its operational health. While solar energy absorbed by a chassis-mounted solar panel is the primary power source for planetary rovers, some systems have the luxury of a backup battery that is rechargeable via the solar panel. This facilitates regulation of available on-board power. Since designing space electronic systems in which all key components share common operating temperature ranges is a non-trivial task, internal temperature regulation is often necessary during rover operations. The implementation of homeostatic power and temperature regulatory mechanisms is only briefly considered at this stage, guided by examples described in [7,8] but implemented using fuzzy sets. In particular, we define a health or operational readiness metric, ORM, as a fuzzy relational function of battery charge level $Battery$ and internal chassis temperature $Temp$. This ORM is used as a basis for making intelligent decisions about homeostatic regulation. As an example, consider the ORM as a linguistic variable represented by fuzzy sets with labels LOW, HIGH. Also, consider the fuzzy sets in Fig. 2 defined over appropriate universes of discourse for $Battery$ (normalized) and $Temp$. These fuzzy sets permit formulation of decision rules such as: IF $Battery$ is HIGH AND $Temp$ is NOMINAL, THEN ORM is HIGH. Status conditions for which the consequent proposition of this rule does not apply, i.e., ORM is LOW, signal a need to execute activities such as temperature regulation and/or battery charging. In this way, intelligent self-regulation decisions can be made based on the imprecise states of relevant linguistic variables. Examples of the most basic homeostasis activities/decisions are:

- IF $Battery$ is LOW, stop vehicle motion to recharge batteries via the solar panel.
- IF $Temp$ is TOO-HIGH, stop vehicle motion to cool down, or turn on internal fans.
- IF $Temp$ is TOO-LOW, turn on internal heater(s).

In addition to active maintenance of internal health, it is necessary to autonomously react to the external effects caused by physical interactions between the rover and rugged terrain. The attitude (pitch and roll) of the vehicle chassis with respect to an inertial reference frame can be monitored in order to avoid instabilities associated with ascent/descent of slopes, traversal of rocky terrain, and turning subject to vehicle curvature constraints. The type and condition of the terrain surface also provides clues for safety assessment. Human automobile drivers are able to perceive certain road conditions (e.g., oil slicks, potholes, and ice patches) as measures of safety, and react to them in order to reduce the risk of potential accidents. In a similar manner, rover potential safety can be inferred and reacted to based on knowledge of the terrain type or surface condition.

The safety module employs concise fuzzy control behaviors that provide approximate reasoning to facilitate maintenance of stable vehicle attitude and wheel traction on rough terrain that is very local to the rover. Note that the strategic navigation module (via the traverse-terrain behavior, Fig. 1) handles the more forward-looking function of ensuring that the rover does not attempt to traverse terrain regions perceived to have excessive roughness and/or slope [9]. Off-road driving heuristics are used by the safety module to facilitate avoidance of hazardous vehicle configurations and excessive wheel slippage. In each case, the system is designed to produce safe speed recommendations associated with the current perception of the physical safety status of the rover. The result is a rover safety and survival subsystem composed of two fuzzy safety behaviors: attitude management and traction management. These subsystems are discussed in the ensuing sections.

4 Safe attitude behavior

Relative to the indoor mobile robot case, mobility and navigation problems for outdoor rough terrain vehicles are characterized by significantly higher levels of difficulty and increased measurement uncertainty. This is due to the fact that complex motions outside of the ground plane occur quite frequently as the vehicle traverses undulated terrain, encountering multi-directional impulsive and resistive forces throughout. In addition, common mobility and navigation sensors often inadequately handle the tremendous variability of surface features and properties of outdoor terrain. Despite these complications, sufficient measures must be taken to maintain upright stability of the vehicle.

For monitoring chassis attitude, a two-axis inclinometer/tilt sensor can be used to measure pitch and roll angles relative to a Cartesian reference frame that is aligned with the rover chassis coordinate frame when the vehicle rests on a level surface. With such a sensor, perhaps the simplest approach is to stop rover motion when either axis senses tilt beyond a critical threshold. In a few instances this "wait and see" binary approach may be sufficient. More often than not, however, dynamic effects such as momentum will quickly defeat the simplest approach and cause the rover to reach marginal stability (a point at which the vehicle begins to tip over), or worse yet, to actually tip-over. Even though planetary rovers typically drive at low speeds (e.g., maximum average speed of ≈ 0.3 m/s), more sophistication is required beyond binary threshold reactions. Instead of allowing the vehicle to wait for the roll or

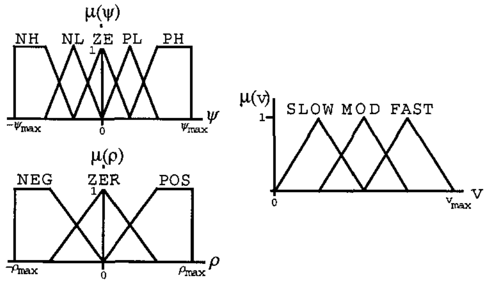
Table 1
Speed Control Heuristics for Off-Road Driving

Vehicle or driving condition	**Recommended speed**
Vehicle pitch/roll	Proportional to pitch/roll
Vehicle maximum pitch/roll reached	Zero (or very slow)
Driving uphill with high traction	Slow
Driving uphill with low traction	Moderate (to avoid irrecoverable wheel slippage)
Driving downhill	Moderate (to avoid wheel sliding)
Driving with low traction (on slippery terrain)	Very slow (to minimize wheel slippage)

pitch to build up to a dangerous threshold before reacting, we have elected to formulate a safety strategy in which the recommended safe speed for the rover is gradually modulated in reaction to changes in attitude. When the rover travels on a relatively level surface, a maximum safe speed is recommended. As pitch and/or roll approaches extremes near marginal stability, gradual reductions in safe speed are recommended (culminating at halted motion). At attitudes between these extremes, recommended safe speeds are computed by interpolation via fuzzy sets and logical inference.

By considering various off-road driving heuristics as a knowledge base for traversing rock-fields, and hills (up-, down-, and side-hill) [5], a set of fuzzy logic rules is formulated to maintain stable rover attitudes for safe navigation. Table 4 lists some of the heuristics for off-road speed control that are reflected in the fuzzy control rules for attitude management and traction management (discussed later). The allowable ranges of pitch and roll are partitioned (based on subjective assessment of the problem and the vehicle specifications) by fuzzy sets to express the approximate nature of the measurements.

The fuzzy set membership functions and fuzzy logic rule base for the stable attitude control behavior are shown in Fig. 3, where the rover speed v is the output and the rover pitch ϕ and roll ρ are the inputs. In the figure, positive and negative are abbreviated by "NEG" and "POS", respectively. Vehicle pitch is represented by five fuzzy sets, while roll is partitioned using three fuzzy sets. Finer granularity of fuzzy subset partitions is used for pitch since the wheelbase (front-rear wheel distance) of our test vehicle is smaller than its track (left-right wheel distance) and therefore, the vehicle is more sensitive to pitch than to roll. Pitch and roll states are used to infer rover speed, which is represented by three fuzzy sets as shown in Fig. 3. Bounds on the allowable ranges for attitude measurements are chosen in accordance with the rover stability constraints and the level of acceptable risk. A static stability analysis of a low-speed vehicle yields the critical attitude angles corresponding to the maximum slopes (longitudinal and lateral) that the vehicle could stand on without tipping over. These are the actual critical pitch/roll angles that correspond to marginal stability. As an added safety measure, they are scaled down using scalar safety factors to determine the bounds (ϕ_{max} and ρ_{max} in



ρ \ ψ	NH	NL	ZE	PL	PH
NEG	SLOW	MOD	MOD	MOD	SLOW
ZER	MOD	MOD	FAST	MOD	MOD
POS	SLOW	MOD	MOD	MOD	SLOW

Fig. 3. Safe attitude membership functions and rules.

Fig. 3) that constrain the universe of discourse. The maximum allowable speed v_{max} is specified according to the application. This design results in a safe attitude behavior that responds early to pitch/roll extremes before marginal stability is reached. The rules in Fig. 3 were derived from interpretation of the off-road driving heuristics of Table 4. In addition to these rules, a crisp rule is applied to set rover speed to zero in the extreme cases when near-marginal stability is reached and the safest reaction is to stop its motion. However, in contrast to the binary threshold scheme mentioned earlier, as marginal stability is approached the rover speed is smoothly decreased to near zero due to the interpolation provided by the fuzzy logic rules.

5 Safe traction behavior

In the absence of some measure of control, wheeled vehicles are prone to loss of traction under certain terrain conditions. On dry paved roads, traction performance is maximal for most wheeled vehicles due to the high coefficient of friction/adhesion between the road and the tread. On off-road terrain, however, a variety of surface types are encountered on which rover wheels are susceptible to slippage. Loss of traction due to excessive wheel slippage can lead to wheel sinkage and ultimately vehicle entrapment. Frequent loss of traction during a traverse from one place to another will also detract significantly from the ability to maintain good position estimates. To improve rover performance, a mechanism for regulating or mitigating wheel slippage is highly desirable.

5.1 Sensing and perception issues

Traction control is a common problem in automobile and general transportation vehicle design with a variety of effective solutions. Solutions are often derived from analyses based on the following equation for wheel slip ratio, λ_s, which is defined non-dimensionally as a percentage of vehicle forward speed,

v [10]:

$$\lambda_s = \left(1 - \frac{v}{r_w \omega_w}\right) \times 100 \qquad (2)$$

Here, r_w is the wheel radius and ω_w is the wheel rotational speed. Equation 2 expresses the normalized difference between vehicle and wheel speeds. When this difference is non-zero, wheel slip occurs. The objective of traction control is to regulate λ_s to maximize traction. This is a relatively straightforward regulation task if v *and* ω_w are both observable. The wheel rotational speed ω_w is typically available from shaft encoders or tachometers. However, it is often difficult to measure the actual over-the-ground speed v for off-road wheeled vehicles. Nonlinearities and time-varying uncertainties due to wheel-ground interactions further complicate the problem. Effective solutions have been found for automotive applications. In fact, fuzzy logic is a common tool for anti-lock (deceleration) and anti-slip (acceleration) control as demonstrated in recent work [11–13]. In these cases, measurement of v is facilitated by the even surface on which the vehicle travels, or by special sensing arrangements. In [11], an accelerometer is used to measure vehicle speed and the slip ratio is estimated based on deceleration of the four wheels. In [12], the measurement of vehicle speed is facilitated by the use of magnetic markers alongside the road in an intelligent highway automation system. In this case, the vehicle speed is measured according to travel time between markers. For application to an electrically driven locomotive, the solution in [13] makes use of a model of the friction-slip relationship, which is fixed for the wheel-rail interaction. On outdoor terrain, the friction-slip relationship varies with surface type. In large part, the available solutions are not directly transferable to off-road vehicle applications in which the terrain is uneven as opposed to being relatively flat, as is the case for automobiles and locomotives.

The use of an accelerometer to measure off-road vehicle speed is problematic since the gravity effects of traversing longitudinal and lateral slopes will interfere with the measurement. For an accelerometer used to measure horizontal acceleration, any off-horizontal vehicle tilt will be sensed as a change in acceleration; as a result, the integrated velocity will be in error. This is realized in [14] where an alternative traction control concept for rovers is considered. In that case, a non-driven "free wheel" is proposed for measuring actual over-the-ground vehicle speed. Alternative ground speed sensors include laser and microwave Doppler effect velocimeters, which can be oriented toward the ground ahead of the vehicle. These have yet to be evaluated by the authors for compliance with the various practical rover constraints on power and mass, as well as the characteristics of errors caused by frequent wheel reactions to rough terrain. Another promising solution is proposed for rovers with an articulated chassis, which enables active control of the vehicle center of gravity. For those vehicles, the use of accelerometers in conjunction with rate gyroscopes is suggested [15].

In our work, we have elected to take a simple linguistic approach that does not rely on accurate sensing of over-the-ground vehicle speed. Instead, visual perception of terrain texture is used to infer an appropriate speed of traversal. Results from traction tests performed on the actual rover are used to determine appropriate speeds for a variety of potential surface types. In particular, the rover is tested on different terrain surfaces (e.g., sand, gravel, densely packed soil, etc.) to determine the maximum speeds achieved before the onset of wheel slippage. These tractive speeds are designated by fuzzy linguistic labels CAUTIOUS, SUBDUED, NOMINAL to be discussed later. Given this information, commanded vehicle speed can be modulated during traversal based on visual classification of the terrain surface type in front of the rover. This is analogous to the perception-action process that takes place when a human driver notices an icy road surface ahead and decelerates to maintain traction. For a rover, such speed modulation allows management of traction by mitigating the risk of wheel slippage. The approach is similar in spirit to other fuzzy logic and dynamic feedback control methods [16,17] proposed for appropriately distributing wheel motor torques to improve traction, albeit, after the onset of wheel slip.

Given the results of actual traction tests, the formulation of fuzzy logic rules to achieve speed modulation is relatively straightforward. The success of the traction management approach depends more heavily on the ability to perceive and classify the various terrain surface types. The problem of off-road surface type identification is formidable for systems equipped with only proximity sensors, range-finders, and/or tactile probes. However, visual image-based classification has been found to be particularly promising [18]. We will now describe an artificial neural network solution to this problem that provides qualitative information about the expected surface traction of terrain immediately in front of the rover. This information is used to infer tractive rover speeds via fuzzy inference.

5.2 Visual traction classification

Distinct terrain surfaces reflect different textures in visual imagery. The ability to associate image textures to terrain surface properties such as traction, hardness, or bearing strength has clear benefits for safe autonomous navigation. To provide this capability, we make use of an on-board camera pointed such that its field-of-view (FOV) covers the ground area in front of the rover as illustrated in Fig. 4. The automated method of classifying terrain surface type is based on a texture analysis approach using an artificial neural network (ANN) — "a computational structure inspired by the study of biological neu-

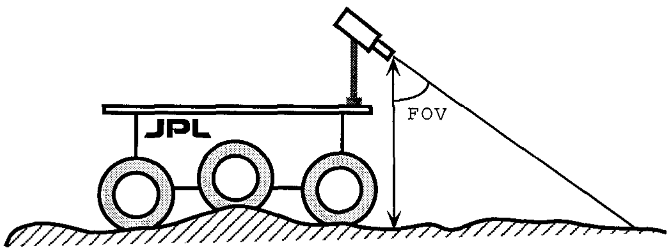


Fig. 4. Camera mounted on rover.

ral processing." With appropriate training, ANNs can be used to represent arbitrary input-output relationships. Based on typical surfaces that the rover may encounter, three different texture prototypes are selected to train a neural network: sand, gravel, and compacted soil. The method involves identifying the different textures by implementing the following strategy:

- Extract a set of 40×40 image blocks from imagery data.
- Reduce image data dimensionality using orthogonal sub-space projection.
- Train a neural network classifier on a set of texture prototypes projected on the eigenvector set.
- During run-time, feed projected texture images to trained neural network.
- Extract texture prototype output from network and classify ground surface type.

Assuming the section of the image just ahead of the front wheels is free of obstacles, a set of 40×40 pixel image blocks is randomly selected from a camera image of size 320×280 pixels. To reduce the large data dimensionality inherent in typical vision-based applications, a filtering step is performed using a standard technique called Principal Component Analysis (PCA) [19]. PCA is a linear optimal method for reducing data dimensionality by identifying the axis about which the desired feature set varies the most. This orthogonal sub-space projection of the image subset permits effective extraction of features embedded in the surface image data set in real time. This technique reduces the dimensionality of the image set while preserving as much of the signal as possible. PCA computes a set of orthonormal eigenvectors (filters) of a data set that captures the greatest correlation between features. The filters associated with a given feature set are derived from the distribution of potential dynamic features embedded in the images. To characterize the distribution of these features, the covariance matrix, R, is found for image subsets containing the desired dynamic features. The following eigenvector problem is solved to derive the set of filters, $\mathbf{w}$, used in our algorithm to maximize the greatest correlation between features:

$$R\mathbf{w} = \lambda\mathbf{w} \tag{3}$$

A total of 30 eigenvectors are used to reduce the 40×40 image block (1600 pixel values) to a pattern set of 30 values (Fig. 5). This reduced data set is then used to train an ANN (Fig. 6) to associate texture with several surface types. For our algorithm, the network output provides the qualitative information needed to make any necessary adjustments to wheel speed in order

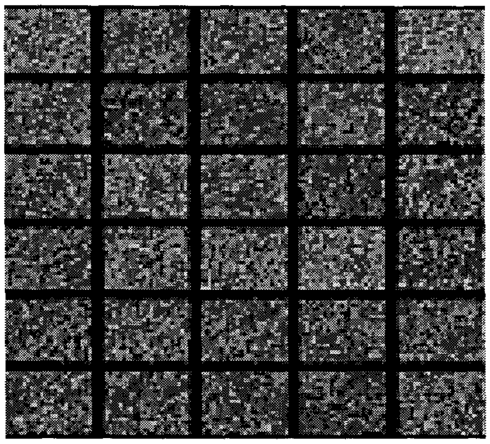


Fig. 5. Texture prototype eigenvectors.

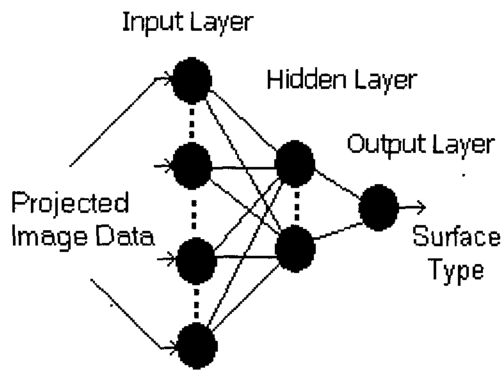


Fig. 6. ANN for surface classification.

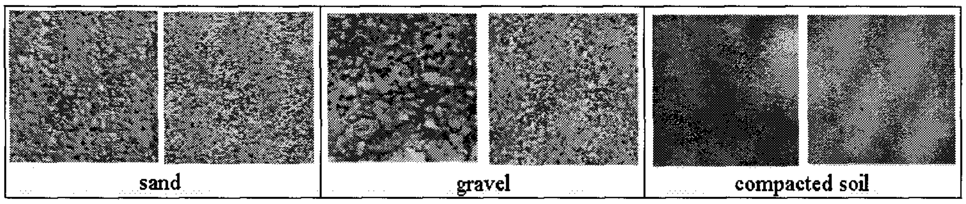


Fig. 7. Terrain surface images classified by the ANN.

to maintain traction on the classified surface. After training the network on typical image data representing different surface prototypes, we utilize it to classify the surface types during run-time. Fig. 7 shows several images of real terrain data properly classified by the trained ANN; these images were not included in the data set used to train the ANN.

5.3 Speed control for traction management

The ANN is trained to provide texture prototype outputs in the unit interval [0, 1], with 0 corresponding to surfaces of very low traction (e.g., ice) and 1 corresponding to surfaces of very high traction (e.g., dry cement). This is a design decision motivated by a desire to establish some intuitive correlation to actual wheel-terrain coefficients of friction. In this way, we can make a qualitative association between output of neural networks and expected terrain traction in front of the rover. We will refer to the texture prototype output as the *traction coefficient*, denoted by C_t.

Wheel-terrain friction coefficients for a variety of tread and surface types are widely published in the literature on vehicle mechanics. However, published friction coefficients for identical tread and surface types vary from source to source. This is due to the fact that measured values depend heavily on the variety of tests and test conditions from which they are generated. Nevertheless, common ranges of friction coefficients for given tread and surface types

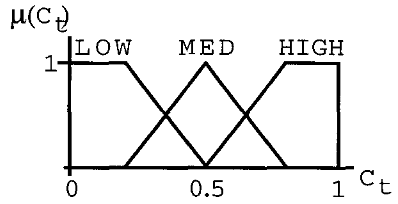


Fig. 8. Fuzzy sets for traction coefficient.

are widely agreed upon. The following are typical estimates of the friction coefficients for rubber tires on various surfaces [10,20]: icy road/snow (0.1), sand (0.3), slippery/wet road (0.4), hard unpaved road (0.65), grass (0.7), dry paved road (0.8–1.0).

Given the uncertainty in associating exact friction coefficients with certain terrain surface types, and the loose correlation provided by the traction coefficient using neural networks, we elect to reason about traction using fuzzy logic. The range of traction coefficients, [0,1], obtained from the ANN is partitioned using three fuzzy sets as shown in Fig. 8. Based on these definitions, the following simple fuzzy logic rules are applied to manage rover traction on varied terrain:

- IF C_t is LOW, THEN v is CAUTIOUS.
- IF C_t is MEDIUM, THEN v is SUBDUED.
- IF C_t is HIGH, THEN v is NOMINAL.

Thus, this design dictates modulation of safe speeds in proportion to expected terrain traction in front of the rover. While the membership functions for CAUTIOUS, SUBDUED, NOMINAL are defined on the same universe of discourse as SLOW, MODERATE, FAST (see Fig. 3), the supports of these membership functions span different subsets of the universal set of rover speeds. However, the shapes of the membership functions for the rover speed are similar to those shown in Fig. 3.

It is noted that for traction management, the membership functions for the rover speed v are based on results of prior traction tests described in Section 5.1. Thus, membership function definitions are vehicle-dependent and reflect knowledge derived from non-slip speeds achieved when the vehicle was tested on various terrain surfaces. For best results, traction tests should be performed on surfaces that represent the expected roughness, hardness, and slope variations of the rover operating environment. Indeed, rover attitude on sloped terrain influences traction. Relationships between attitude and traction are evident in the last several heuristics listed in Table 4, and these are reflected in the rules of the safety behaviors. Although our solution decouples reasoning about attitude and traction, the overall vehicle response is determined by combining reactions to both as discussed in the next section. Also of note is the fact that the neural network could have been trained to map its inputs directly to the actual range of tractive speeds (rather than the range of C_t). However, in this approach fuzzy inference serves to account for uncertainties in both the surface classification and the subsequent specification of tractive speed.

6 Coordinating fuzzy safety behaviors

The rover speed recommendations inferred by the stable attitude and traction behaviors are used to compute a resultant safe speed recommendation, v_{safe}, which is issued at each control cycle. Individual safety behavior recommendations can be combined using several alternative computations on crisp or fuzzy set outputs. We describe two computational formulations employed in our work. Perhaps the simplest, most conservative and cautious approach is to compare the crisp (defuzzified) outputs of the stable attitude and traction behaviors, and select the minimum of the two as v_{safe}. In this way, the safety module recommends the slowest rover speed that is expected to mitigate wheel slip and maintain a stable attitude. However, by making use of defuzzified safety behavior outputs before computing the resultant recommendation, a certain amount of useful information is lost from the control decision process. Each rule base produces a resultant fuzzy set from the aggregation of individual fuzzy logic rule consequents. The output fuzzy set of each safety behavior represents a possibility *distribution* of preferential safe speeds for maintaining either attitude or traction. When defuzzified independently, the useful information contained in each possibility distribution is collapsed into a single crisp number. The minimum of the crisp outputs then determines the preference for achieving the dual objectives of maintaining stable attitude and traction for the rover. In some cases this approach may be overly conservative, forcing the vehicle to exhibit a timid behavior and traverse terrain at very slow speeds in situations where extreme caution is not warranted. This could have the effect of trading off reasonable mission/task execution duration for overly cautious behavior. It can be argued, as the saying goes, that it is better to be safe than sorry. This is true; however, we can do better while still maintaining acceptable levels of risk. The richer body of information contained in each possibility distribution can be fully exploited by fusing the fuzzy behavior outputs using fuzzy set theoretic computations to produce resultant safe speed recommendations as formally explained below.

6.1 Behavior fusion

Each rover safety behavior is synthesized as a set of n fuzzy rules of the form given by Equation 1, where we recall that X and U are the input and output universes of discourse, respectively. Formally, the output of the i-th fuzzy rule is represented by a fuzzy relation, $\tilde{u}_i \in X \times U$, which is a fuzzy set itself. Moreover, the output of the fuzzy rule-base can be characterized as a single fuzzy relation, $\tilde{v}$, which is a union of fuzzy relations $\tilde{u}_i$, $i = 1, 2, \ldots, n$. The output of a fuzzy behavior then, can also be represented as a fuzzy set, which in this case is a possibility distribution of safe speed preferences reflecting the point of view of a given safety behavior.

Let $\tilde{v}_A$ and $\tilde{v}_T$ represent the fuzzy outputs of the stable attitude and traction behaviors, respectively. Each of these fuzzy behavior outputs is represented by a possibility distribution, which contains information that is useful for deciding what the most appropriate safe speed should be. In order to make full use of the information produced by the safety behaviors, we aggregate their fuzzy outputs to yield a resultant fuzzy set, $\tilde{v}_S = \tilde{v}_A \cup \tilde{v}_T$. This aggregated fuzzy set represents a consensus of the preferences of each contributing behavior [21,22]. Defuzzification to compute v_{safe} is deferred until after the aggregation takes place.

$$v_{safe} = \frac{\int u \mu_{\tilde{v}_S}(u)}{\int \mu_{\tilde{v}_S}(u)}; \ \forall u \in U \tag{4}$$

While this fusion of behavior outputs allows control decision-making by consensus, we can also impose a bias towards the preferences of one behavior over the other by introducing scalar weights to express relative importance. Since we consider the maintenance of stable attitude to be more important than traction losses for the rover, we tailor the behavior fusion formulation such that the following holds,

$$\tilde{v}_S = (\alpha_A \tilde{v}_A) \cup (\alpha_T \tilde{v}_T); \ \alpha_A, \alpha_T \in [0, 1] \tag{5}$$

with $\alpha_A > \alpha_T$. Thus, fuzzy outputs of the safety behaviors are modulated according to relative importance in Equation 5 and used to compute recommended safe rover speeds using Equation 4. The fuzzy set union of behavior output recommendations often results in an overlapping of portions of and $\tilde{v}_A$ and $\tilde{v}_T$. When so-called *weight counting* defuzzification [23] methods are employed, membership values in the overlapping region are counted twice – once for $\tilde{v}_A$ and once for $\tilde{v}_T$. This ensures that all safe speed preferences recommended by both behaviors are factored into the control decision, thus forming a true consensus. In Equation 5, we elect to aggregate the modulated fuzzy outputs using a t-conorm that will preserve the information contributed by each behavior. The arithmetic sum t-conorm, and hence, Center-of-Sums defuzzification [23], has been chosen for this purpose due to its weight counting property. Mizumoto refers to this fuzzy control reasoning method as the product-sum-gravity method, and describes the weight counting concept as an emphatic effect on the fuzzy inference result [24]. The arithmetic sum, as an aggregation operator, affords a behavior coordination strategy that retains and uses all available information from the individual output fuzzy sets. It is argued in [24] that this method produces more intuitive control results than the commonly used min-max-gravity method due to Mamdani [25]. Using Equations 4 and 5 with fuzzy union by the arithmetic sum, the crisp control recommendation issued at each control cycle by the safety module is computed as follows.

$$v_{safe} = \frac{\int u \cdot [(\alpha_A \cdot \mu_{\tilde{v}_A}(u)) + (\alpha_T \cdot \mu_{\tilde{v}_T}(u))]}{\int [(\alpha_A \cdot \mu_{\tilde{v}_A}(u)) + (\alpha_T \cdot \mu_{\tilde{v}_T}(u))]}; \; \forall u \in U \tag{6}$$

In this formulation, we have used multiplicative weights to express the relative importance of the safety behaviors in the aggregated control decision. In general, operators other than multiplication can be used to achieve a similar effect. Yager [26] refers to such operators as importance transformations and suggests a general class of them for both t-norm and t-conorm aggregations. Similar ideas have been formally expressed in the more general context of multi-attribute decision-making [27].

6.2 Navigation system interface

As mentioned earlier, in the context of the overall navigation system, the safety reasoning module focuses on vehicle survivability and health, while the strategic navigation module focuses on mission and goal-directed motion from place to place [9]. The control interface between the safety module and the strategic navigation module is depicted in Fig. 9. The internal structure of the safety module is shown as well, where the speed decision block can be configured for behavior fusion (Equation 6) or the more conservative minimum speed selection described earlier. As shown in the diagram, the overall safe speed recommended by the safety module is compared to the strategic speed recommendation. The smaller of the two is taken as the safest speed and is issued as the commanded set-point $\bar{v}$ for translational motion control. Note that the commanded rotational velocity $\bar{\omega}$ of the rover is unaffected by v_{safe} in the current implementation.

Determination of v_{safe} is independent of the behavior fusion process used to compute strategic navigation speeds that result from recommendations issued by the navigation behaviors (see Fig. 1) [9]. This is an important feature, as it allows recommended safe speeds to override strategic speeds, if necessary, to ensure vehicle safety. This effect is achieved by the "min" operation on resultant safe speed and resultant navigation speed. The argument presented above regarding intra-module loss of information when using the "min" op-

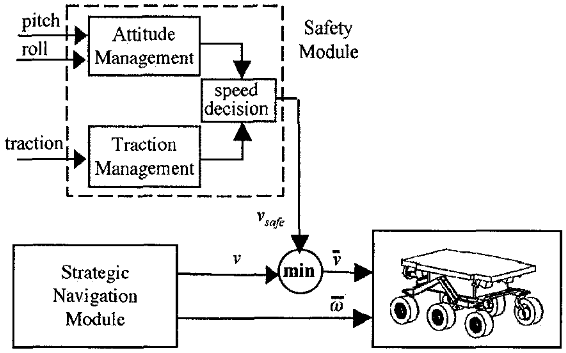


Fig. 9. Safety and strategic navigation control interface.

erator on crisp behavior outputs does not hold at the module interface. This is due to the fact that behaviors within a given module recommend actions toward a shared multi-objective goal — vehicle safety in one case and strategic navigation in the other. So while it is possible to fuse fuzzy behavior outputs across all modules, such that safety behavior outputs are fused with navigation behavior outputs, this is not recommended. Such a distribution of speed control across all system behaviors makes it difficult to ensure that the inter-behavioral interactions will yield an overall safe speed of traversal [28].

7 Field tests and experimental results

In this section, we describe two field tests and associated laboratory experiments performed to evaluate the effect of the safe attitude and traction behaviors. The first test considers reactions to rover pitch and roll during traversal. The second test is concerned with mitigation of wheel slippage. As a test rover, we used the Pioneer All-Terrain (AT) mobile robot platform, a commercially available robot designed for rough terrain mobility. The rover hardware is enhanced with additional on-board computing (Pentium II laptop), a vision system for real-time terrain assessment, and a tilt sensor (see Fig. 10). The Crossbow Technology, Inc. model CXTA02 inclinometer is used, which has a $\pm 75^o$ range and 0.05^o resolution. The ground-facing camera on the front of the rover is mounted $0.3m$ above the ground, tilted downward 45^o with a 45^o FOV. This camera enables surface traction classification (cameras for strategic navigation are mounted on the raised platform).

7.1 Safe attitude test

An obstacle-free swath of undulated terrain is chosen to test the safe attitude behavior. The rover is commanded to traverse the swath with and without the behavior activated. Without active safe attitude management, the rover

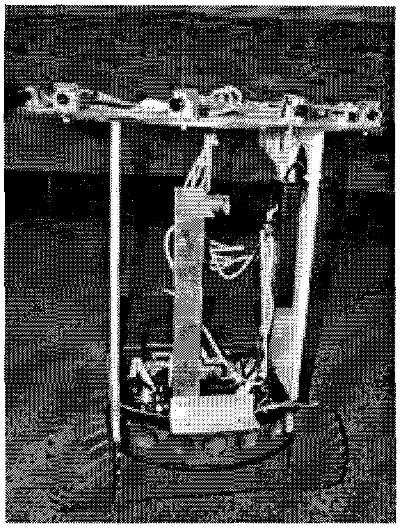


Fig. 10. Pioneer-AT rover with enhancements.

Fig. 11. Effect of stable attitude control.

traverses the terrain at a nominally fast speed recommended by the strategic navigation system based on the fact that no significant obstacles are present. With active attitude management, the rover traverses the terrain at various reduced speeds in response to changes in its pitch and roll according to the fuzzy logic rules in Fig. 3. This reactivity reduces the risk of approaching marginal tilt stability, which leads to tip-over. It also enhances the ability of rigid-suspension vehicles (such as the Pioneer-AT) to maintain wheel contact with the ground. A comparative effect of the stable attitude behavior is shown in Fig. 11. The left picture corresponds to the test without active attitude management; it shows a case where the rover's rear-right wheel loses contact with the ground. The right picture shows the rover at the same approximate location with all wheels in contact with the ground while actively modulating its speed to maintain stable attitude.

To further illustrate the effect of safe attitude management, we exercise the component in a laboratory experiment where the rover traverses a swath of terrain for 10 meters. Synthetic attitude measurements are generated by sinusoidal functions of random amplitude to emulate changes in pitch and roll experienced on a hypothetical undulated and rough terrain. The amplitudes are uniformly distributed random numbers bounded by the maximum stable

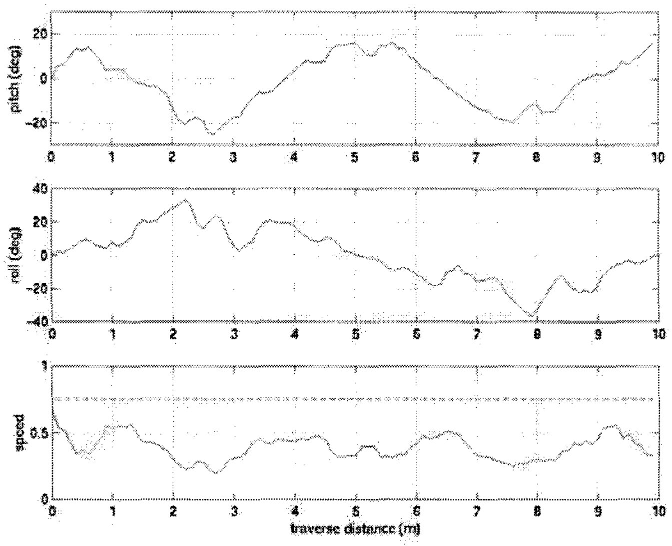


Fig. 12. Speed modulation for attitude management.

pitch and roll of the rover. It is assumed that the strategic navigation module recommends a constant normalized speed of 75% (of maximum allowable speed) throughout the traverse. The results of this experiment are shown in Fig. 12 in plots of pitch, roll, and v_{safe} (normalized) versus distance. The strategic speed is shown in the speed-distance plot as a dashed line. Observe that v_{safe} is modulated low in response to near-extreme attitudes. This is most apparent when both pitch and roll are simultaneously large in magnitude. Also observe that v_{safe} is consistently lower than the strategic speed, thus exhibiting the caution of the safety module in reaction to cognizance of vehicle safety.

7.2 Safe traction test

A similar comparative field test and laboratory experiment is performed to test safe traction management. A benign portion of terrain comprising two distinct surface types (hard compacted soil and gravel) is chosen on which the rover will be susceptible to wheel slippage when traversing the surface transition at nominally fast speeds. The scenario is depicted in Fig. 13 where the rover is about to transition from a hard compacted soil to gravel surface. The rover is commanded to traverse the transition with and without the safe traction management behavior activated. Without active traction management, the rover traverses the terrain at a nominally fast speed. With active traction management, the rover reduces its speed upon encountering a surface of lower perceived traction (as classified by the vision-based ANN described earlier) according to the fuzzy logic rules presented in Section 5.3. This reactivity mitigates the risk of excessive wheel slippage during transitions between, and traversal on, surfaces of different traction characteristics.

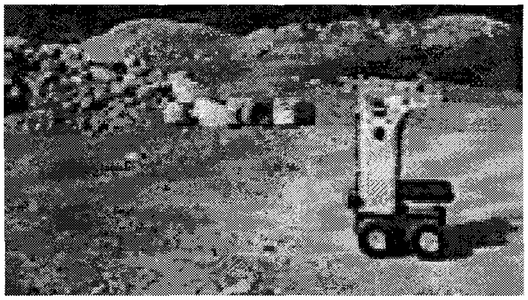


Fig. 13. Rover approaching surface type transition.

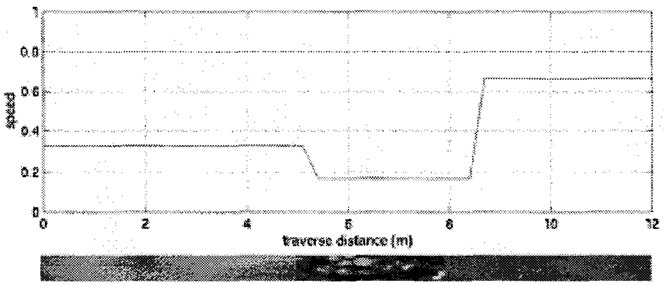


Fig. 14. Speed modulation for traction management.

To further illustrate the effect of the safe traction management, we exercise the component in a laboratory experiment where the rover traverses a 12 meter swath of terrain consisting of different surface types for which the traction coefficient C_t is 0.5 for $5m$, 0.2 for $3m$, and 0.9 for $4m$. We assume, for the sake of discussion, that these values correspond to sand, gravel, and concrete, and that the surface texture camera has a ground surface view horizon out to $0.3m$ in front of the rover wheels. In this experiment, the strategic navigation module recommends a constant normalized speed of 80% throughout the $12m$ traverse. The result is shown in Fig. 14 where the traction coefficient and recommended rover speeds are plotted versus distance. The images of the three terrain surface types corresponding to distance are inset in the figure as well. As expected, changes in perceived traction result in reactive management of the safe speed recommended by the safe traction behavior to avoid the risk of excessive wheel slippage. Note that our laboratory experiment accounts for a reaction delay between classification of the surface type and the actual change in set-points for v_{safe}. As in the previous example, v_{safe} is consistently lower than the strategic speed, thus exhibiting the caution of the safety module in reaction to cognizance of changing "road" condition.

8 Discussion and conclusions

For rover operation over extended time and distance, some capacity for built-in safety and health cognizance is required. The necessary capacity must support real-time navigation and the complete system must be realizable in practical rover computing hardware. This paper describes how a nominal level of safety assurance can be achieved with intuitive fuzzy logic rules for approximate reasoning and intelligent control. Basic approximate reasoning is used for self-regulation of power and internal temperature to actively maintain operational health. Safe attitude and traction management behaviors of the safety module combine to provide active countermeasures to potential vehicle tip-over and excessive wheel slippage. Initial tests in outdoor fields validate the utility of the proposed approach. However, additional laboratory and field testing is warranted to obtain statistical performance ratings with respect to a larger variety of terrain types and field conditions.

The safety module presented herein is limited in that, currently, it only considers a subset of relevant vehicle health and safety indicators that effect off-road robotic vehicles. Additional indicators requiring active countermeasures include component failures, potential chassis high-centering, wheel sinkage, and vehicle dynamic constraints. Closer attention should be paid to dynamic stability, particularly when applying the approach for faster vehicles than typical planetary rovers. The effectiveness of the traction management approach depends upon the nominal speed of rover traversal, the perceptual FOV of the ground-facing camera, and the speed at which the image processing can be done to support the neural network traction classifier. The computational speed at which traction classifications can be made must be fast enough to allow effective speed control reactions at the rover's nominal speed. Due consideration of these additional effects, within observability constraints of the system, should be the focus of future enhancements.

Using the proposed approach, the capabilities presented in this paper can be combined with appropriate countermeasures to additional health and safety conditions. This will lead to survivable rover systems that are of practical use for performing long-duration missions involving traversal over challenging and high-risk terrain.

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