MULTI-RANGE TRAVERSABILITY INDICES FOR TERRAIN-BASED NAVIGATION

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Abstract

This paper presents novel measures of terrain traversability at three different ranges; namely Local, Regional, and Global Traversability Indices. The Local Traversability Index is related by a set of linguistic rules to local obstacles and surface softness within a local perception range, measured by on-board sensors mounted on the robot. The rule-based Regional Traversability Index is computed from the terrain roughness and slope that are extracted from video images of the terrain within a regional perception range obtained by on-board cameras. The Global Traversability Index is obtained from the terrain topographic map, and is based on the natural or man-made surface features such as mountains and craters within a global perception range. Each traversability index is represented by four fuzzy sets with the linguistic labels {POOR, LOW, MODERATE, HIGH}, corresponding to surfaces that are unsafe, moderately-unsafe, moderately-safe, or safe for traversal, respectively. These indices are used to develop a behavior-based navigation strategy for a mobile robot traversing a challenging terrain. The traversability indices form the basis of three navigation behaviors; namely, Traverse-Local, Traverse-Regional, and Traverse-Global behaviors. These behaviors are integrated with the Seek-Goal behavior to ensure that the mobile robot reaches the goal safely while avoiding obstacles and impassable terrain segments. The paper is concluded by an illustrative graphical simulation study [1].

[1]The research described in this paper was performed at the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration.

1 Introduction

Exploration of planetary surfaces and operation in rough terrestrial terrain have been strong motivations for research in autonomous navigation of field mobile robots in recent years. These robots must cope with two fundamental problems. The first problem is to acquire and analyze the terrain quality information on-line and in real time, and to utilize it in conjunction with limited prior terrain maps. The second problem is to deal with imprecision in sensor measurements and uncertainty in data interpretation inherent in sensing and perception of natural environments. With respect to these two fundamental problems, outdoor robot navigation defines a research topic that is more challenging than indoor robot navigation in structured and benign man-made environments.

Robust on-line terrain characterization and traversability assessment are clearly core research problems for autonomous field robot navigation. Two types of solutions have been proposed by researchers at CMU and JPL. In the CMU methods [1-4], the terrain traversability is computed along different candidate paths that correspond to different robot steering angles. The traversability of each path is determined mathematically by a weighted sum of the roll, pitch, and roughness of the grid-based map cells along that path, incorporating their certainty values [1]. The JPL rule-based approach [5-10] takes a sharp departure from analytical methods and is centered on the *Fuzzy Traversability Index.* This index is a novel concept that was first introduced in [5-6] as a simple *linguistic* measure for quantifying the suitability of the regional terrain for traversal by a mobile robot. This perceptual approach to terrain assessment is highly robust to measurement noises and interpretation errors because of the use of fuzzy sets in a linguistic rule-based system.

Earlier papers by JPL researchers [5-8] have focused on *regional* terrain characterization and traversability assessment. In this paper, the regional traversability index concept is extended to both *local* and *global* terrain, to complement the regional measure. The three traversability indices are then used to develop a behavior-based navigation strategy for mobile robots. The paper is structured as follows. Sections 2-4 discuss terrain traversability analysis at local, regional, and global ranges. The navigation behaviors based on these measures are presented in Section 5. Section 6 discusses the integration of multiple behavior recommendations for robot navigation. An illustrative simulation study is presented in Section 7. The paper is concluded in Section 8 with a review of key features.

2 Local Traversability Analysis

For local traversability analysis, we focus on the terrain quality in close proximity of the mobile robot up to a distance R_l, where R_l is the *local perception range* of the robot[2]. Different measures of local terrain quality can be considered for this purpose. In this section, we consider two attributes of the local terrain that contribute to its traversability, namely local obstacles and surface softness, as described below.

2.1 Local Obstacles

Local obstacle is the generic term that refers to large rocks ("positive" obstacles) or deep ditches ("negative" obstacles) that are impassable by the robot. The presence of obstacles can be detected in real-time by proximity sensors (for rocks) and cameras (for ditches) mounted on the robot [8]. Each local sensor (such as proximity sensor or camera) measures the distance d_o between the robot and the *closest* obstacle within its range of operation, and this information is continously updated during robot motion. The closest obstacle distance d_o is represented by three fuzzy sets with the linguistic labels $\{VERY-CLOSE, CLOSE, DISTANT\}$, with the trapezoidal membership functions shown in Figure 1a.

[2]This range is less than or equal to the sensing envelope of the on-board local sensors, and is typically about 0.5 meters for a small-sized robot.

2.2 Surface Softness

Local surface softness directly affects the traction of a mobile robot traversing a challenging terrain. Different ground material, whether soft sand, loose gravel, or compacted soil, exhibit different contributions to the robot's ability to travel effectively on the surface.

There are several methods for assessing the surface softness in close proximity of the robot. A viable method to determine the surface type, and as a result the surface softness, is based on visual texture analysis using neural networks [8]. This is a two-step approach; in the first step a neural network classifier is trained off-line using a set of known sample texture prototypes. In the second step, the trained neural network is used to recognize the ground texture acquired during run-time. The perceived surface type is then fed into a look-up table for obtaining surface softness γ. This softness factor is characterized by three fuzzy sets with the linguistic labels $\{SOFT, MEDIUM, HARD\}$, with the trapezoidal membership functions shown in Figure 1b.

2.3 Local Traversability Index

Once the characteristics of the local terrain are obtained in terms of the closest obstacle distance d_o and local surface softness γ, this information can be incorporated into a single index of local traversability τ_l. This index is represented by four fuzzy sets with the linguistic labels $\{POOR, LOW, MODERATE, HIGH\}$, with the trapezoidal membership functions shown in Figure 1c. The relationship between the Local Traversability Index τ_l and the obstacle distance d_o and surface softness γ is expressed by a set of simple linguistic fuzzy logic rules. These rules are summarized in Table 1, with d_o and γ as two inputs and τ_l as the single output. Observe that *precise* measurements of the obstacle distance and surface softness are *not* needed, because of the multi-valued nature of the linguistic fuzzy sets used to describe them.

3 Regional Traversability Analysis

The regional traversability covers a zone of up to a distance R_r from the robot, where R_r is the *regional perception range* of the robot[3]. The physical and geometrical qualities of the terrain segment within this zone determine its ease-of-traversal by the mobile robot. Several characteristics of the terrain can be considered for this purpose. The most notable ones are the terrain slope and roughness. These two characteristics are extracted from video image data obtained by the stereo cameras mounted on the mobile robot, as described in [8]. Once the characteristics of the viewable scene are extracted, the slope and roughness values are converted into memberships of the fuzzy sets $\{FLAT, SLANTED, SLOPED, STEEP\}$ and $\{SMOOTH, ROUGH, BUMPY, ROCKY\}$, respectively. The Regional Traversability Index τ_r is represented by four fuzzy sets with the linguistic labels $\{POOR, LOW, MODERATE, HIGH\}$, and is obtained from the rule set summarized in Table 2.

4 Global Traversability Analysis

In previous sections, we present local and regional traversability analyses using on-board sensors, with typical ranges of 0.5 meters and 5 meters for a small-sized robot. In this section, a different type of terrain traversability is discussed which is based on the *terrain map* and can operate in the global range in tens of meters resolution, well beyond the robot's sensing envelope.

The new concept of *Fuzzy Traversability Map* is introduced here. This map classifies the terrain segments based on how difficult and unsafe each segment is for traversal by the mobile robot. The map building process involves two steps. We first identify relevant topographic terrain features (such as ravines, mountains, and valleys) as observed in aerial imagery or obtained from land surveys. Various image-based techniques can be used to identify these relevant terrain features. Once the relevant topographic terrain features are extracted, they are fed into a linguistic rule set for constructing the Fuzzy Traversability Map. This rule set assigns a traversability index to each terrain segment that reflects the global-scale terrain quality for traversal. The segment classification can be performed using four fuzzy sets with the linguistic labels $\{POOR, LOW, MODERATE, HIGH\}$, as in Sections 2-3. Each traversability class designates the traversal risk/difficulty associated with that segment, namely unsafe, moderately-unsafe, moderately-safe, and safe. For example, IF *Mountain Slope* is STEEP, THEN *Traversability* is POOR.

A convenient representation of the Fuzzy Traversability Map is the *Fuzzy Traversability Grid*. The grid is obtained by overlaying on the traversability map an mxn grid composed of mn equal-sized grid cells, where m and n are user-defined numbers chosen based on the map resolution and the robot footprint. Each grid cell is assigned a traversability index that reflects the *minimum* index of all terrain segments occupying that cell.

4.1 Global Traversability Index

Once the Fuzzy Traversability Map and Grid are generated, we can compute the Global Traversability Index of the mobile robot in different terrain sectors at any time. For this purpose, we proceed as follows:

- Decompose the terrain available to the mobile robot into several circular sectors centered at the current robot position and having radius R_g. The value of R_g determines the *global perception range* of the robot, and is the distance at which we wish the robot to react to the global surface features.

- For each circular sector, assign the *minimum* traversability index of the map segments contained within that sector, as shown in Figure 2. This can be obtained using geometric calculation of the intersections between the sector and the segments. The rationale for using the minimum index is to enhance robot safety, given the fact that the map information and terrain classification are often inaccurate and approximate.

The outcome of this procedure is the Global Traversability Index τ_g that corresponds to a particular terrain sector.

[3]This range is less than or equal to the sensing envelope of the on-board regional sensors, and is typically about 5 meters for a small-sized robot.

5 Terrain-Based and Goal-Based Navigation Behaviors

The control variables of the mobile robot are the translational speed v and the rotational speed (or turn rate) ω, where $v = \sqrt{(\frac{dx}{dt})^2 + (\frac{dy}{dt})^2}$, $\omega = \frac{d\theta}{dt}$, and x, y, and θ are the position coordinates of the robot center and the robot orientation in a fixed user-defined reference frame, respectively. The robot speed v is represented by the four linguistic fuzzy sets $\{STOP, SLOW, MEDIUM, FAST\}$. Similarly, the robot turn rate ω is represented by the three linguistic fuzzy sets $\{NEG, ZERO, POS\}$, where NEGative and POSitive turn the robot to left and right directions, respectively.

We shall now describe three terrain-based and one goal-based behaviors that constitute the robot navigation system. This system is an extension of the behavior-based navigation system described in [9-10].

5.1 Traverse-Terrain Behaviors

Three independent behaviors are now defined based on the three traversability analyses; namely, traverse-local behavior, traverse-regional behavior, and traverse-global behavior. These behaviors issue motion recommendations to the robot control system on the basis of the local terrain, regional terrain, and global terrain quality information, respectively. We shall now use the traversability indices discussed in Sections 2-4 to develop simple linguistic rules for determination of the robot motion (i.e., turn rate and speed) while moving on natural terrain. It is assumed that the robot can only move in the forward direction (i.e., reverse motion is not allowed). The terrain in front of the robot is partitioned into three groups of 60° circular sectors as shown in Figure 3, namely: front, right, and left of the robot. The local, regional, and global circular sectors have the radii R_l, R_r, and R_g, which are the local, regional, and global perception ranges, respectively. Each perception range defines the domain-of-operation of the corresponding traverse behavior. The Traversability Indices for the three regions, τ^f, τ^r, τ^l, are assumed to be inferred from sensory data (for local and regional behaviors) or from the traversability map (for global behavior).

We shall now develop a set of linguistic rules for robot motion based on the terrain traversability indices. We treat local, regional, and global traversability indices in a unified manner by describing a "universal" set of rules for all three terrain-based navigation behaviors. These three behaviors are separated out in the integration section later.

5.1.1 Turn Rules

The terrain-based turn rules are summarized in Table 3. These rules are analogous to the steering actions of a human driver during an off-road driving session. Notice that a turn maneuver is not initiated when either the front region is the most traversable, or the right and left regions have the same traversability indices as the front region. Observe that the "preferred" turn rate is chosen arbitrarily to be NEG, i.e., when the robot needs to turn to face a more traversable region, it tends to turn left.

5.1.2 Move Rules

The robot speed v is determined based on the front traversability index τ^f, i.e. the quality of the terrain sector facing the current robot heading. This determination is formulated as a set of simple fuzzy logic rules for speed of traverse as follows:

- IF τ^f is POOR, THEN v is STOP.
- IF τ^f is LOW, THEN v is SLOW.
- IF τ^f is MODERATE, THEN v is MEDIUM.
- IF τ^f is HIGH, THEN v is FAST.

This is analogous to a human driver adjusting the car speed based on the surface conditions.

5.2 Seek-Goal Behavior

The seek-goal behavior is a *map-based* behavior whose objective is to navigate the mobile robot from a known initial position to a user-specified goal position disregarding the terrain quality. The turn and move rules for the Seek-Goal behavior are the same as those given in [9-10].

6 Integration of Multiple Behaviors

In this section, we integrate navigational recommendations from the two *sensor-based* behaviors (traverse-local and traverse-regional) with the two *map-based* behaviors (traverse-global and seek-goal).

Let the weighting factors l^w, r^w, g^w, and s^w represent the strengths by which the traverse-local, traverse-regional, traverse-global, 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 $\{LOW, NOMINAL, HIGH\}$. Four sets of weight rules for the four behaviors are now presented.
The seek-goal weight rules are as follows:

- IF d is VERY-NEAR, THEN s^w is HIGH.
- IF d is NOT VERY-NEAR, THEN s^w is NOMINAL.
- IF τ_l^f is POOR, THEN s^w is LOW.

where d is the robot distance to goal with the fuzzy classes {VERY-NEAR, NEAR, FAR}. The traverse-local weight rules are as follows:

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

The traverse-regional weight rules are as follows:

- IF d is NOT VERY-NEAR AND τ_l^f is NOT POOR, THEN r^w is HIGH.
- IF d is VERY-NEAR OR τ_l^f is POOR, THEN r^w is NOMINAL.

The traverse-global weight rules are as follows:

- IF d is NOT VERY-NEAR AND τ_l^f is NOT POOR AND τ_r^f is NOT POOR, THEN g^w is HIGH.
- IF d is VERY-NEAR OR τ_l^f is POOR OR τ_r^f is POOR, THEN g^w is NOMINAL.

At each control cycle, the above sets of weight rules are used to calculate the four crisp weighting factors using the Center-of-Gravity (Centroid) defuzzification method [11]. The motion recommendations from the seek-goal, traverse-local, traverse-regional, and traverse-global behaviors are then weighted by the corresponding gains s^w, l^w, r^w, and g^w respectively prior to defuzzification, as shown in Figure 4. The final motion commands are computed using the Center-of-Gravity defuzzification method as:

$$\bar{v} = \frac{s^w \Sigma v_p^s A_p^s + l^w \Sigma v_p^l A_p^l + r^w \Sigma v_p^r A_p^r + g^w \Sigma v_p^g A_p^g}{s^w \Sigma A_p^s + l^w \Sigma A_p^l + r^w \Sigma A_p^r + g^w \Sigma A_p^g}$$

$$\bar{\omega} = \frac{s^w \Sigma \omega_p^s B_p^s + l^w \Sigma \omega_p^l B_p^l + r^w \Sigma \omega_p^r B_p^r + g^w \Sigma \omega_p^g B_p^g}{s^w \Sigma B_p^s + l^w \Sigma B_p^l + r^w \Sigma B_p^r + g^w \Sigma B_p^g}$$

In the above equations, v_p and A_p are the peak membership value and the truncated area under the membership function for the velocity fuzzy sets, while ω_p and B_p are the corresponding values for the turn rate fuzzy sets.

7 Simulation Study

The Robot Graphical Simulator is a software package developed at JPL for 2D visualization of the robot motion using the reasoning and decision-making capabilities of the fuzzy logic navigation strategy. The map of the terrain on which the robot moves is available *a priori* and is converted to a Fuzzy Traversability Map in which terrain traversability is graded using the four linguistic fuzzy sets $\{POOR, LOW, MODERATE, HIGH\}$. In the simulation study, the terrain is composed of the following four regions:

- *Plain*: A land area having a level surface with no major hazards and HIGH Traversability Index. Unless stated otherwise, the plain covers the entire ground surface in the simulation.
- *Crater*: A crater has POOR Traversability Index. The location and size of the crater are known *a priori* to the mobile robot through the previously-acquired Fuzzy Traversability Map. The crater is reflected in the Global Traversability Index.
- *Region of High Rock Concentration*: The size and location of the region on the terrain are *not* known *a priori*. This region is detected by on-board cameras that are modeled in the software. The region is reflected in the Regional Traversability Index.

- *Large Rocks*: The rock sizes and locations on the terrain are *not* known *a priori* to the mobile robot. These rocks are detected by on-board proximity sensors modeled in the software. The rocks are reflected in the Local Traversability Index.

Several simulation scenarios were carried out using the Robot Graphical Simulator, and a typical run is reported here. Figure 5 shows the terrain on which the robot travels and the robot initial and goal positions. The Traverse-Local, Traverse-Regional, Traverse-Global, and Seek-Goal behaviors are invoked to navigate the robot safely to its destination while avoiding both rocks and both impassable regions. The path traversed by the robot under the fuzzy logic navigation rules is shown by the dotted line in Figure 5. It is seen that the test is successfully completed with the robot reaching its goal safely while avoiding all hazards.

8 Conclusions

Multi-range traversability indices are introduced in this paper for a field mobile robot operating on a challenging natural terrain. These indices quantify the difficulty/risk associated with the robot mobility at three different ranges. Using Local, Regional, and Global Traversability Indices, three navigation behaviors are developed that together with the goal-seeking behavior comprise the robot navigation strategy. This navigation strategy provides a framework for smooth integration of *sensor-based* behaviors such as Traverse-Local and Traverse-Regional with *map-based* behaviors such as Traverse-Global and Seek-Goal. The navigation strategy is demonstrated by a graphical simulation study. Current research is focused on implementation and field testing of the methodology described in this paper on a commercial mobile robot.

9 References

1. S. Singh, et al: "Recent progress in local and global traversability for planetary rovers", Proc. IEEE Intern. Conf. on Robotics and Automation, vol. 2, pp. 1194-1200, San Francisco, 2000.
2. A. Kelly and A. Stentz: "Rough terrain autonomous mobility", Journal of Autonomous Robots, vol. 5, no. 2, pp. 129-198, 1998.
3. R. Simmons, et al: "Experience with rover navigation for Lunar-like terrains", Proc. IEEE/RSJ Intern. Conf. on Intelligent Robots and Systems (IROS), pp. 441-446, Pittsburgh, 1995.
4. D. Langer, J. K. Rosenblatt, and M. Hebert: "A behavior-based system for off-road navigation", IEEE Trans. on Robotics and Automation, vol. 10, no. 6, pp. 776-783, 1994.
5. H. Seraji: "Traversability Index: A new concept for planetary rovers", Proc. IEEE Intern. Conf. on Robotics and Automation, vol. 3, pp. 2006-2013, Detroit, 1999.
6. H. Seraji: "Fuzzy Traversability Index: A new concept for terrain-based navigation", Journal of Robotic Systems, vol. 17, no. 2, pp. 75-91, 2000.
7. A. Howard, H. Seraji, and E. Tunstel: "A rule-based fuzzy traversability index for mobile robot navigation", Proc. IEEE Intern. Conf. on Robotics and Automation, vol. 3, pp. 3067-3071, Seoul (Korea), 2001.
8. A. Howard and H. Seraji: "Vision-based terrain characterization and traversability assessment", Journal of Robotic Systems, vol. 18, no. 10, pp. 577-587, 2001.
9. H. Seraji, A. Howard, and E. Tunstel: "Safe navigation on hazardous terrain", Proc. IEEE Intern. Conf. on Robotics and Automation, vol. 3, pp. 3084-3091, Seoul (Korea), 2001.
10. A. Howard and H. Seraji: "An intelligent terrain-based navigation system for planetary rovers", IEEE Robotics and Automation Magazine, vol. 8, no. 4, pp. 9-17, 2001.
11. K. M. Passino and S. Yurkovich: "*Fuzzy Control*", Addison-Wesley Publishing Company, CA, 1997.

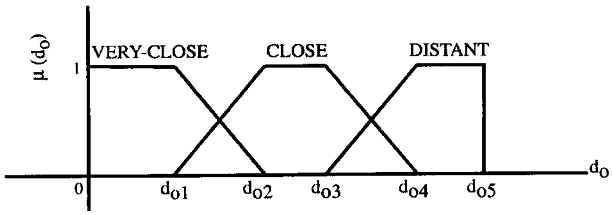

Figure 1a. Membership functions for closest obstacle distance d_O

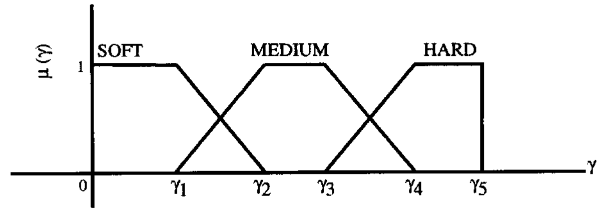

Figure 1b. Membership functions for surface softness γ

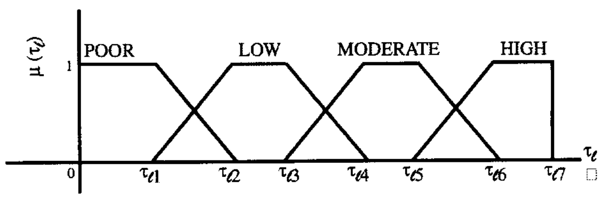

Figure 1c. Membership functions for Local Traversability Index τ_ℓ

Surface Softness \ Closest Obstacle Distance	Distant	Close	Very-Close
Hard	High	Moderate	Poor
Medium	Moderate	Low	Poor
Soft	Poor	Poor	Poor

Table 1. Rule set for Local Traversability Index

Terrain Slope \ Terrain Roughness	Smooth	Rough	Bumpy	Rocky
Flat	High	High	Moderate	Poor
Slanted	High	Moderate	Low	Poor
Sloped	Moderate	Low	Low	Poor
Steep	Poor	Poor	Poor	Poor

Table 2. Rule set for Regional Traversability Index

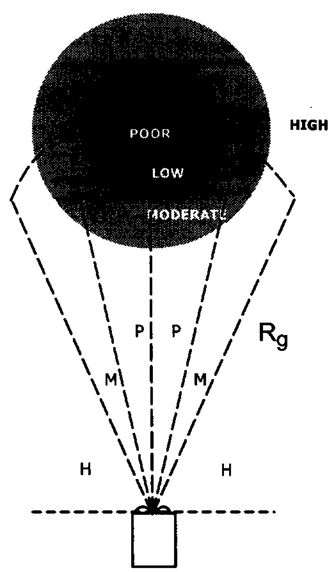

Figure 2. Determination of Global Traversability Index

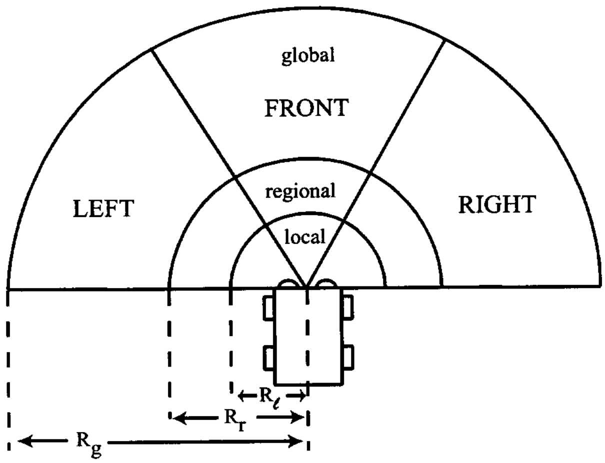

Figure 3. Definition of available regions

τ^f = poor

τ^ℓ \ τ^r	high	moderate	low	poor
high	N	N	N	N
moderate	P	N	N	N
low	P	P	N	N
poor	P	P	P	Z

τ^f = low

τ^ℓ \ τ^r	high	moderate	low	poor
high	N	N	N	N
moderate	P	N	N	N
low	P	P	Z	Z
poor	P	P	Z	Z

τ^f = moderate

τ^ℓ \ τ^r	high	moderate	low	poor
high	N	N	N	N
moderate	P	Z	Z	Z
low	P	Z	Z	Z
poor	P	Z	Z	Z

τ^f = high

τ^ℓ \ τ^r	high	moderate	low	poor
high	Z	Z	Z	Z
moderate	Z	Z	Z	Z
low	Z	Z	Z	Z
poor	Z	Z	Z	Z

Table 3. Turn rules for the traverse-terrain behaviors (P=POS, N=NEG, Z=ZERO)

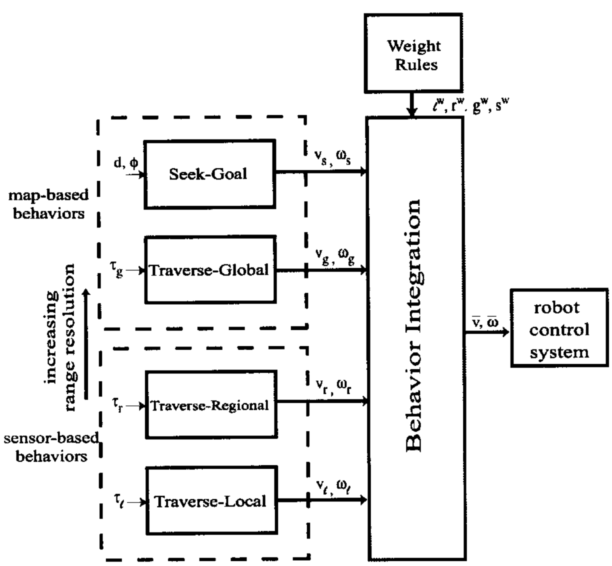

Figure 4. Block diagram of the robot navigation system

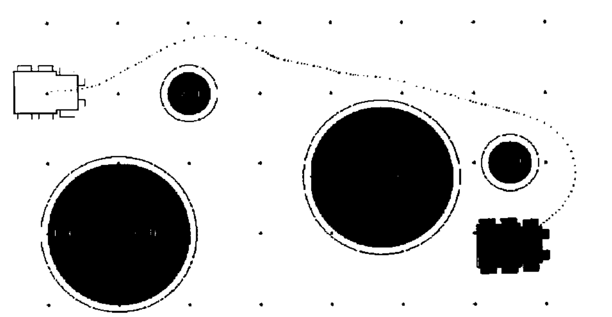
Figure 5: Robot path using the fuzzy logic navigation strategy