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Goal-Enhancement Technique for Fuzzy Terrain-Based Navigation

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Abstract. This paper presents a simple reactive terrain navigation strategy for a shape-shifting tracked mobile robot on environments consisting of flat surfaces, discrete climbable steps and slopes. The proposed navigation strategy employs the concept of fuzzy Terrain Traversability Index, where the ease of traversal is evaluated from a combination of geometric properties. In the two-layer fuzzy controller, the Terrain Traversability Index is first computed based on slope gradient and step height, of which data is obtained from an a priori information of its surroundings in the form of a 2.5D grid map, before combined with sonar sensory data to determine the overall traversability of the region. Using goal-enhancement on fuzzy sets prior to defuzzification, the fuzzy controller outputs a turn recommendation which is deemed most convenient for the mobile robot. The navigation algorithm has been implemented into a virtual agent and case studies. These studies have shown encouraging results of the ability of the mobile robot to select its path based on its perceived ease of traversing

Keywords: Mobile robot navigation, Terrain, Traversability Index, Fuzzy sets and Fuzzy logic controller.

1. Introduction

Autonomous navigation on uneven Terrains can be classified into various classes depending on the environment as well as the robot's structural capability. Seraji[1] proposed the novel concept of rule-based fuzzy Terrain Traversability Index for planetary rovers. This method provides an intuitive way of capture human perception into the system without the need for complex mathematical modeling. This concept is originally meant for choosing the best paths for the robot in field environments to prevent track slippage-induced odometry errors on uncharted environments [2]. The idea is applicable even for ordinary navigation in indoor environments [3]. Ye et al. [4] also came up with a similar concept, albeit more mathematical and uses the Polar Traversability Index calculated from the robot's estimation of terrain slope and roughness based on heights of every cell in a terrain patch and also takes the differences between grids of adjacent height into the calculations.

Behavior-based navigation strategies are some of the more popular approaches to terrain-based navigation [5-7], whereby individual behaviors such as goal-seeking, traverse-terrain, avoiding obstacles, etc perform turn recommendations for the robot. There are also methods which generate candidate arcs and then selecting the best arc trajectory based on either the shortest path or the one with least cost [8, 9]. These heuristic methods involve using parallel search algorithms and genetic algorithm planners [10]. This research study attempts to use the method similar to those described in [11, 12] by attempting to steer a shape-shifting tracked robot equipped with sonar sensors. The navigation strategy comprises of a two-level fuzzy inference system to produce an output value of the Terrain Traversability Index.

2. Theoretical Work

The *Traversability Index (TI)* of each region is evaluated in the form of a double-layered fuzzy inference system (FIS). The first fuzzy inference layer will output the value of the first Traversability Index τ_{i1} whereas the second layer outputs the value of the second Traversability Index τ_{i2}.

At the first level, the step heights z_{si} and slope gradients g_{si} are the only terrain properties used in the traversability assessment of the robot. Using the concept implemented in [1], the index of terrain quality is done using a *fuzzy inference system (FIS)*, whereby each of the two terrain characteristics stated above are first fuzzified into their fuzzy sets of *{NEUTRAL, MODERATE HIGH}* for *zsi* and *{FLAT, SLOPED, STEEP}* for g_{si}. Next, these fuzzy sets are mapped to the output sets of *Terrain Traversability Index 1*τ_{i1} *{LOW, MEDIUM, HIGH}* via a set of fuzzy relations specified in a Fuzzy Associative Matrix, where each rule follows the form shown below:

If z_{si} *is NEUTRAL AND* g_{si} *is FLAT then* τ_{i1} *is HIGH.*

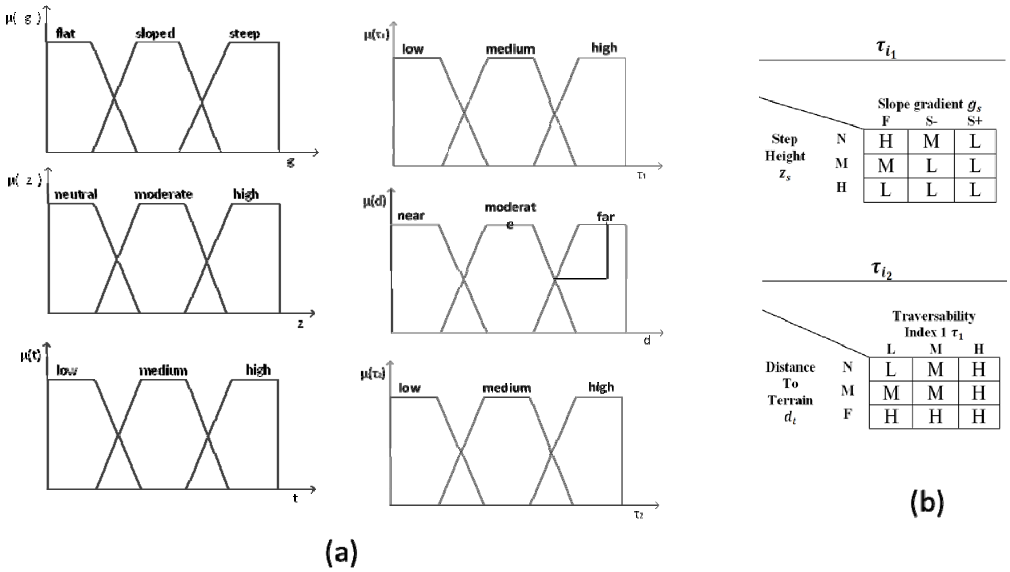


Fig.1. (a) Membership functions for inputs of slope gradient g_{si} step height z_{si} and output Traversability Index 1τ_{si} and (b) Membership functions for inputs of Traversability Index 1 τ_{i1} distance to terrain d_{ti} and output 2 τ_{i2}

The above example obeys the compositional rule of fuzzy inference, and the *AND, OR, NOT* operators are represented by *min, max*, and complement mathematical operators. The inference procedure is followed by the aggregation of the rule consequents. Finally, defuzzification is performed using the *Centre-of-Gravity (COG)* method to generate the first level *Terrain Traversability Index*. In the second level, due to the large assumption made in II(A) where unregistered cells are considered walls, the distance to terrain d_{ti} has also become a contributing factor to determine the traversability index. This implies that the distance between the regions to the robot are calculated based on the robot's self-localization if they contain steps and slopes; otherwise d_{ti} is measured based on readings obtained from the cluster of sonar sensors representing each region. The inputs to the second layer are τi , evaluated from the first layer FIS and also d_{ti} Employing the same method as with layer 1, the inputs are fuzzified, mapped to the output fuzzy sets of *Terrain Traversability Index 2* via another set of fuzzy rules, aggregated and finally defuzzified using the *COG* method.

2.1. Terrain based navigation strategy AND data processing

The crisp values of the Traversability Indices of each region are first normalized according to a number reflecting the highest possible absolute traversability index. It is noted that normalization to only the highest traversability index among the regions is not possible, as this will cause the robot to assume a region is traversable when all regions have low traversability. Next, the values are used as limiters for the fuzzy sets corresponding to the linguistic variable of heading angle:

$$\mu_{C_i'}(\theta) = \tau_{i_2} \tag{1}$$

where   represents the clipping value or saturation point for the membership functions of the fuzzy sets *{LARGE NEGATIVE, SMALL NEGATIVE, ZERO, SMALL POSITIVE, LARGE POSITIVE},* and representing the crisp value of *Traversability Index 2* for each region *i.*

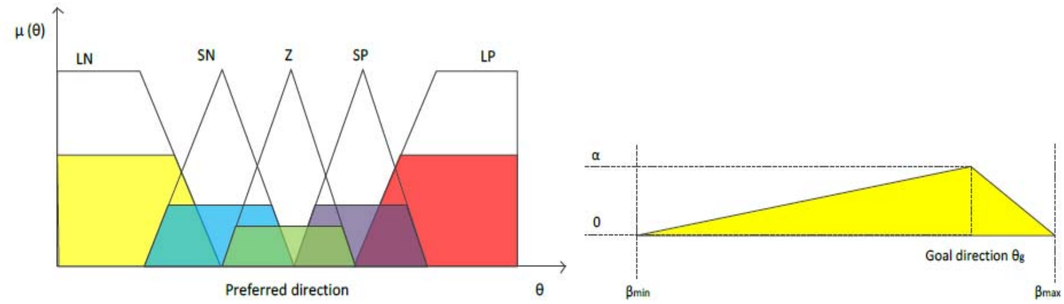


Fig. 2. (a) Aggregated fuzzy sets for the preferred direction of the robot (b) Illustration showing the magnitude of the additional multiplier with respect to the goal. and   represent the boundary for which the influence of the goal should reach in the universe of discourse of θ.

2.2. Goal-Enhancement Technique

This technique involves introducing an *additional multiplier*, whereby the magnitude of the adder increases the closer it is to the goal. The maximum attractive value α is a user-defined value which can be tuned according to how aggressive the controller should be in pursuing the goal. It is noted that it is also possible to define α as a variable dependent on some special requirements e.g. the distance to the goal. However, it is noted that this multiplier cannot be directly applied to the fuzzy sets right away, as it should still give higher priority to avoid obstacles compared to target seeking. Hence, as its name implies this multiplier set needs to be multiplied by the $\mu_C(\theta)$ over the entire continuum C, where C represents the aggregated fuzzy set of the entire output variableθ. The equation for this is shown in (2):

$$\mu_{C_{new}}(\theta) = \begin{cases} \mu_C(\theta) + \alpha\mu_C(\theta) \times \frac{\theta-\beta_{min}}{\theta_g-\beta_{min}} & if\ \theta < \theta_g \\ \mu_C(\theta) + \alpha \quad if\ \theta = \theta_g \\ \mu_C(\theta) + \alpha\mu_C(\theta) \times \frac{\beta_{max}-\theta}{\beta_{max}-\theta_g} & if\ \theta > \theta_g \end{cases} \tag{2}$$

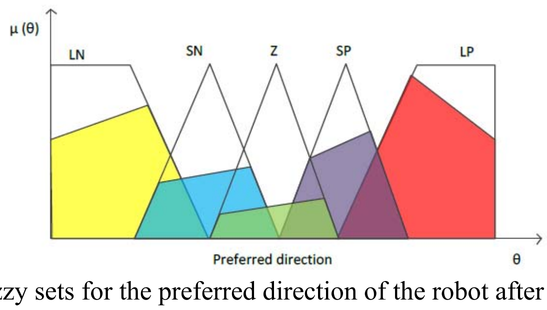


Fig.3.The final aggregated fuzzy sets for the preferred direction of the robot after the goal-enhancement is applied

Defuzzification this time is performed by taking the Centre-of-Largest-Area (CLA) [14] among 3 direction groups (left, front, right). This is due to the fact that in conventional COG calculation, the recommended angle would end up being ZERO in case the final aggregated set is symmetrical like the one in Fig. 4. The ZERO direction in that figure has a LOW traversability and moving in that direction would end up causing collision with the obstacle. The angle command is thus calculated using the equation:

$$\theta_o = \frac{\sum_{\theta=\gamma_{min}}^{\gamma_{max}} \mu_{C_{new}}(\theta)\theta}{\sum_{\theta=\gamma_{min}}^{\gamma_{max}} \mu_{C_{new}}(\theta)}$$

(3)

where γ_{max} and γ_{min} represent the boundaries of the left, zero, or right directions.

3. Simulations

The virtual agent used for simulation was created using the rapid robot prototyping software Webots. At present, the virtual agent is only equipped with encoders for dead reckoning and ultrasonic sensors for detection of obstacles in its surroundings. Some additional sensors are mounted to facilitate edge detection and step negotiation; however these are only meant for reactive control of the robot, hence without the a priori knowledge of steps and slopes in the vicinity the virtual agent will traverse any terrain ahead deemed traversable without regard for its level of difficulty.

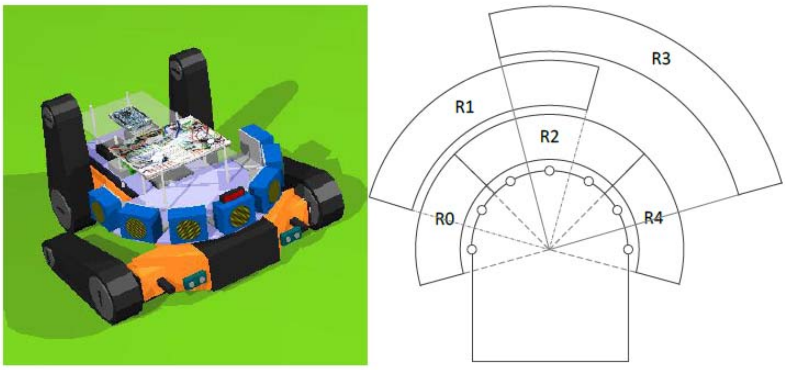
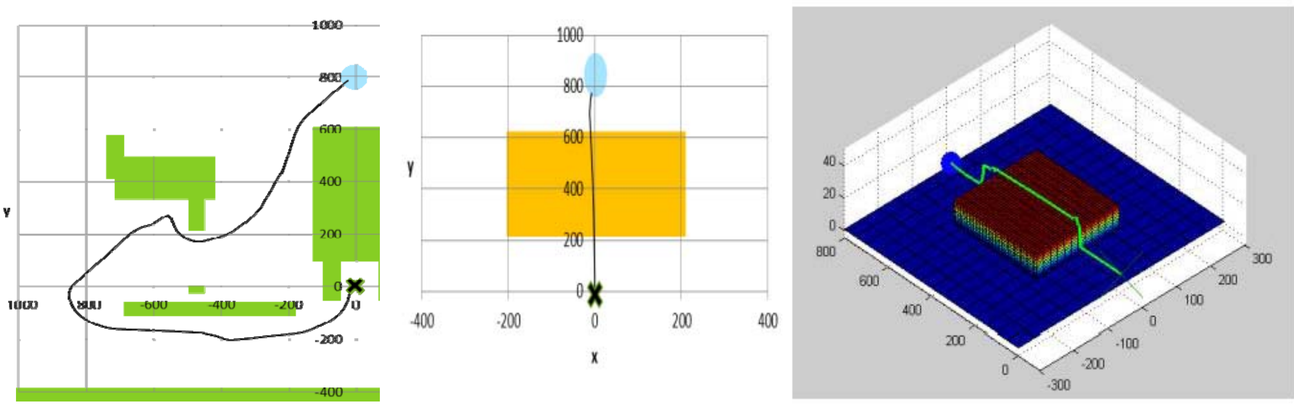


Fig.4.Image on the left shows the virtual agent, image on the right shows the regions corresponding to the cluster of ultrasonic sensors mounted on the robot for obstacle negotiation



Case-1 Case-2

Fig.5.Case-1: Path taken by the virtual agent in the simulated environment; shaded regions represent obstacles. Case-2: Path taken by the virtual agent. Image on the left shows the robot on the 2D Cartesian plane while the image on the right shows the traversing in 3D space.

Case-1: In the first case, all objects encountered are basically obstacles, and hence every region containing an obstacle is considered a region of LOW traversability. There are no steps or slopes and hence the robot has no a priori information of any terrain features. The robot is required to move from its initial position (marked by an X) to the goal (marked by a circle) while avoiding obstacles along the way. At the very start, the robot is facing the direction of the goal, which means it was surrounded by walls. Due to the protective mechanism introduced, the robot recognized the need to turn around to look for alternative paths. It is observed that once the robot has cleared the obstacles, it steers back to the head towards the goal.

Case-2: In the second case, a wide step was generated at some distance in front of the robot's initial position en route to the goal. In this case, the virtual agent has a strengthened resolve to climb the steps as it is right on the direction of the goal. Its aggressiveness to traverse terrains to meet its target can be more easily tweaked by just changing the value of influence of its goal-seeking parameter α.

4. Conclusion

This paper has presented a simple terrain-based navigation strategy by applying a goal-enhancement technique on top of fuzzy logic to determine a robot's motions. Even though simulation results appear promising, the algorithm requires further research and testing to validate its advantage over conventional navigation strategies. Further improvements suggested include implementing the traversal cost function in the algorithm, completing the real-time implementation of the robot for step negotiation and possibly extending the reach of terrainability to traversing stairs, as well as implementing a real-time traversability assessment system to bring the robot a step closer to fully autonomous operation.

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