Reactive Fuzzy Logic Controller Simulation for Robot Motion Planning

B. M. Bhairat[#1], M. R. Gosavi[2], V. M. Thakare[3]

[1]*Department of Mathematics, Br. Balasaheb Khardekar College, Vengurla Dist- Sindhudurg (M.S.)*

[2]*Department of Mathematics, Maharashtra Mahavidyalaya, Nilanga Dist- Latur (M. S.)*

[3]*Department of Computer Science and Technology, Sant Gadage Baba Amravati University, Amravati. (M. S.)*

ABSTRACT

This work discusses the application of fuzzy logic based algorithms to robot motion control and compares their approaches. This application includes robotic vehicle navigation in a 2D environment. The authors create an approach which attempts to overcome this tendency of fuzzy algorithms with a "layered, goal-oriented" navigation strategy. Two layers are proposed: long-range versus short-range information assessment. The first layer uses long-range sensor data and the global goal angle to determine a direction that is both traversable (free of obstacles) and desirable (toward the goal). The second layer takes the way-point formed by the first layer as a sub goal. This layer produces a local trajectory which guides the robot toward the way-point while avoiding collisions with obstacles. A ring of short-range sensors is used to implement a reactive navigation algorithm wherein local direction and speed commands are generated in response to near obstacles as the robot seeks the way-point. Further, it is seen that the layered approach produces a smoother trajectory and avoids obstacles before coming in close proximity to them.

Keywords*: *Fuzzy Algorithms, Layered Approach, Local Trajectory, Navigation, Traversable And Desirable

I. INTRODUCTION

The goal of autonomous robot operation is a topic of considerable research. Robots may frequently find themselves in environments for which a reliable map of obstacles and terrain is unavailable due to the dynamics of the environment, imprecise sensory data or simply a lack of prior knowledge of the environment [1]. In such situations, it may be necessary for a robot to recalculate its trajectory online. While an end-to-end motion plan for the robot in terms of gross motions over longer distances may remain valid, a response to a moving or unforeseen obstacle may force the robot to alter its path in the middle of local obstacles while en route from the initial configuration to the final goal.

Fuzzy algorithms execute in three major stages: fuzzification, inference, and defuzzification. In the fuzzification stage, real world sensory inputs in a given universe of discourse are characterized on the closed interval [0, 1] according to their levels of membership in fuzzy sets. These sets are given names which express qualities of the input variable using easily understood linguistic terms. A membership function maps the value of the input variable to a degree of membership in each of the fuzzy sets. The fuzzified value then, represents the level of truth of each of these linguistic terms for a given input. For example, the angular direction of a near obstacle to a mobile robot might have a universe of discourse of -90° to 90° where 0° denotes the current heading of the robot.

II. PREVIOUS WORK DONE

D. Shi et al. [1] presents Robot Navigation in Cluttered 3D environments using preference-based fuzzy behaviors. K. Tanaka [2] describes an introduction to fuzzy logic for practical applications. X. Yang et al. [3] present a layered goal-oriented planning strategy for mobile robot navigation. P.G. Zavlangas et al. [4] present industrial robot navigation and obstacle avoidance employing fuzzy logic. Also author took the support of Lab VIEW PID Controller Toolkit User Manual [5], National Instruments Corporation, Austin. P. F. Muir et al. [6] presents kinematic modeling of wheeled mobile robots. E. L. Hall et al. [7] describes motion planning using fuzzy logic controller in Robotics: A User-Friendly Introduction. Z. L. Cao et al. [8] presents dynamic omni-directional vision for mobile robots. Z .L. Cao, Y. Y. Huang, and E. L. Hall [9] presents region filling operations with random obstacle avoidance for mobile robots. S. J. Oh et al. [10] presents calibration of an omni-directional vision navigation system using an industrial robot. Kazuo Tanaka [11] presents design of model-based fuzzy controller using Lyapunov's stability approach and its application to trajectory. C. V. Altrock et al. [12] presents advanced fuzzy logic control technologies in automotive applications. B. M. Bhairat et al. [13] describes implementation of crisp logic for robot control. B. M. Bhairat et al. [14] presents mathematical model for trajectory control using fuzzy logic. B. M. Bhairat et al. [15] presents steering mobile robot using fuzzy logic approach.

LIMITATIONS OF PREVIOUS WORK DONE

Fuzzy sets are capable of handling imprecise inputs, in the field of robotics. An input angle be sensed inaccurately, its levels of truth according to the linguistic terms may vary while its relative membership levels in the sets remain qualitatively the same. Generally the fuzzy algorithms can be used to implement efficient control in a variety of settings with little conceptual difference in approach. The limitations of fuzzy algorithms exposed by these articles are, perhaps the more interesting results of the comparison.

III. FUZZY SET DEFINITION WITH FUZZIFIED INPUTS

Sets are often defined to have the piecewise-linear shape shown so as to reduce the computational complexity of determining set membership [6]. Typical shapes include triangular, square, singleton, Gaussian or asymmetric types. Other variables commonly of interest in robotic applications include distance to an obstacle and speed of the robot with respect to an obstacle.

Figure 1 above shows a possible definition of fuzzy sets for how a "crisp" (real world) input angle θ might linguistically reflect the level to which the obstacle is left, in front, or right of the vehicle. Here, an angle of 30° represents a direction having fuzzified degrees membership in the set of angles to the right ("rightness") of μ_R and frontness of μ_F. The inference stage applies the fuzzified input value to a rule base to determine a command output. The rule base contains the operational intelligence of the system.

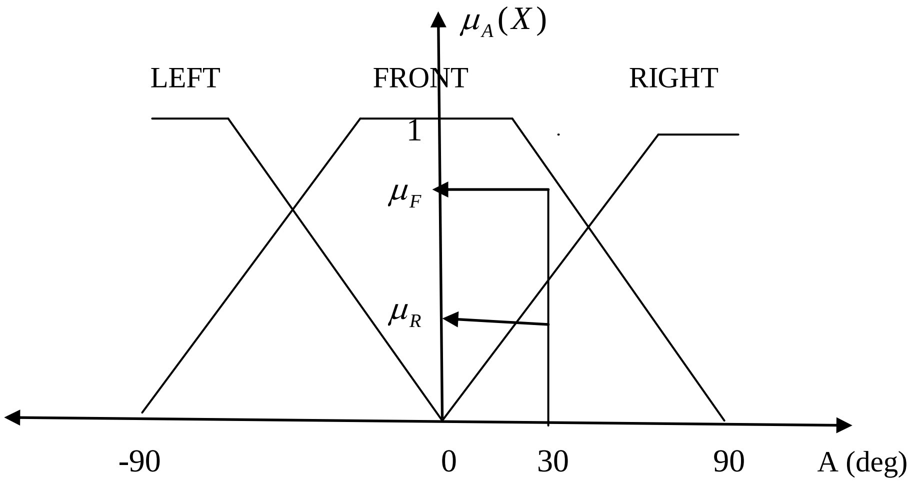

Figure 1. Fuzzy set definition with a fuzzified input

An example rule apply to a mobile robot is given below.

If Obstacle Angle is RIGHT and Distance is NEAR Then
Steering Direction is LEFT_BIG ……………………………………… (1)

A rule base must cover all permutations of input variables having degrees of truth in all possible linguistic terms. Hence the total number of rules *N* which must be represented in a rule base either by explicit statement or default action is given by in the relation:

$$N = \prod_{i}^{m} p_i \quad \text{……………………………… (2)}$$

where *m* is the number of input variables (angle, speed, distance, etc.), and *pi* is the number of linguistic terms for the i^{th} variable [7]. Multiple rules in the rule base may have their predicate conditions satisfied to greater or lesser degrees by fuzzified input variables. Such rules are said to have *fired*. Each fired rule, then, possesses an *adaptability* to the associated output command through the fuzzy operation (AND, OR, sum, bounded sum, product, etc.) stated by the rule (2). The defuzzification stage extracts a crisp command output from inferences drawn from fired rules.

IV. MOBILE ROBOT NAVIGATION IN A 2D ENVIRONMENT

In applications of fuzzy logic to 2D robot motion planning, work in this area is focused on short range reactive control. That is, robots were navigated by simply reacting to near obstacles upon detection while taking into account a global goal direction. While such algorithms have frequently proven effective, they often encounter situations in which the goal configuration becomes unreachable by the robot despite the availability of a traversable path. More commonly, reactive fuzzy navigation may suffer from “shortsighted” behavior wherein the angle to the final goal influences all steering decisions in unison with local sensor data. Situations then arise in which short range sensors may not detect obstacles between the current configuration of the robot and the goal. In these cases, a path may be selected that is less desirable than others available. Figure 2 compares the results of shortsighted behavior to an end-to-end path plan. Through purely reactive short-range fuzzy control, the robot attempts to move in the direction of the goal at point B when obstacle 2 is still out of its perceptive range. The undesirable path ABCDEG is the result. Clearly, with the benefit of long-range planning, path AJKG would be seen as more desirable.

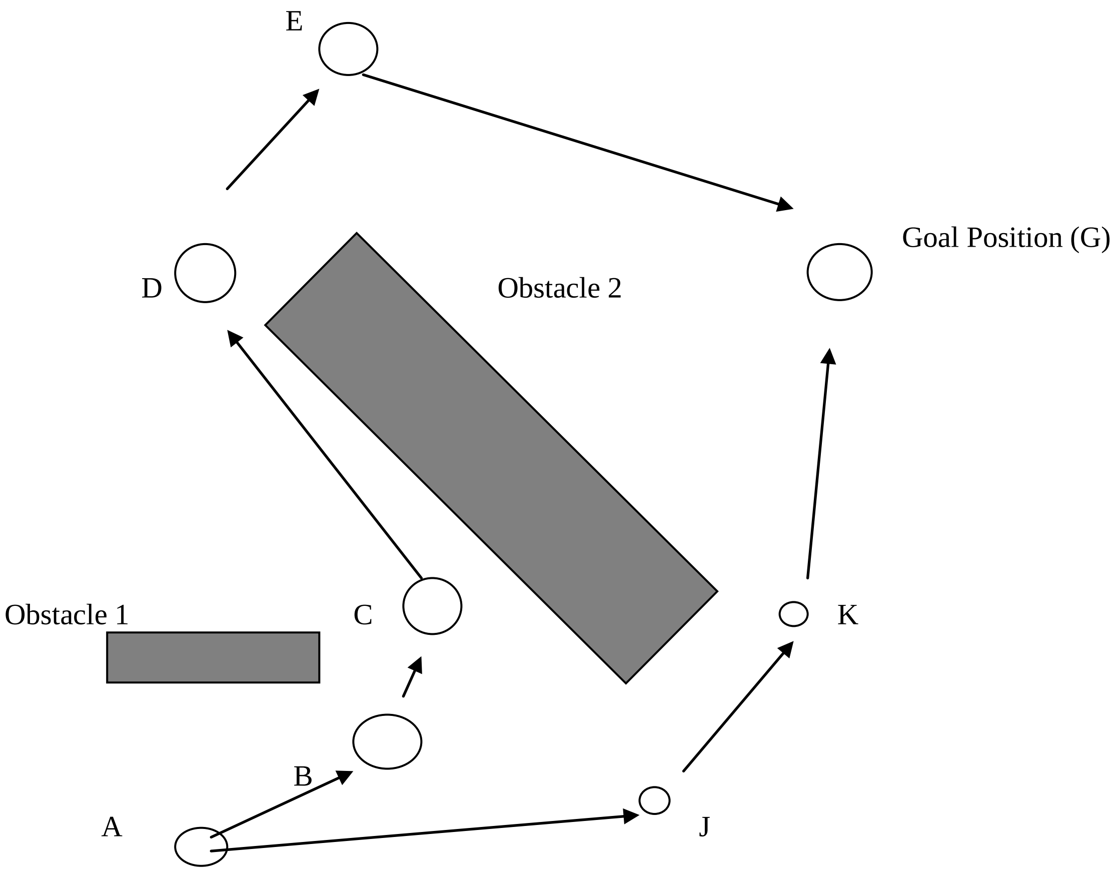

Figure 2 Shortsighted goal-seeking versus long-range path planning.

The authors formulate an approach which attempts to overcome this tendency of fuzzy algorithms with a "layered, goal-oriented" navigation strategy. Two layers are proposed: long-range versus short-range information assessment. The first layer uses long-range sensor data and the global goal angle to determine a direction that is both traversable (free of obstacles) and desirable (toward the goal). The qualities of directional traversability and desirability are represented as fuzzy sets and fused to produce a way-point along the path to the goal. Sensors are positioned at intervals around the perimeter the robot body and detect distant obstacles. The signal strength of each sensor indicates the relative nearness of an obstacle. This strength is fuzzified through a collection of trapezoidal fuzzy sets for angles of -180^0 (left) to +180^0 (right). Where adjacent sensors detect an obstacle with strengths of μ_1 and μ_2, an untraversable area τ_i is the composed fuzzy set found by the bounded sum of the two strengths as given by the equation below.

$$\tau_i = \mu_1 \oplus \mu_2 = \min\{1,\ \mu_1 + \mu_2\} \text{ .... (3)}$$

The *traversable* area Γ is given by the complements of all τ_i as defined by the equation below.

$$\Gamma = \ not \bigcup_{i=1}^{n}\{\tau_i\} = 1 - \max_{i=1}^{n}\{\tau_i\} \text{ .... (4)}$$

where n is the number of activated sensors. The desirability Ω of a potential steering direction is a fuzzified representation of the goal angle ϕ with respect to the current heading of the robot. It is determined by a composed set from the relative strengths (μ_1 and μ_2) of adjacent triangular fuzzy sets at 90^0 intervals on the same universe of discourse as traversability. It is defined by the equation below.

$$\Omega = \mu_1 \cup \mu_2 = sum\{\mu_1,\ \mu_2\} \text{ .... (5)}$$

The direction to the way point is the fuzzy set $\bar{\gamma}$ represented by the intersection of composed sets for traversability and desirability.

$$\bar{\gamma} = \Gamma \cap \Omega = \min\{\Gamma,\ \Omega\} \text{ .... (6)}$$

Over the range of possible angles, the intersection set will have multiple peaks. Each peak will be separated from others by an interval of zero membership since the sets for untraversability have crossing points greater than 0.5. This intersection of composed sets is defuzzified by taking the mean of maximum of the largest area (MOMLA) to generate a crisp angle γ which is the direction to the way-point. This defuzzification technique is a combination of the mean of maximum (MOM) and centroid of largest area (CLA) techniques.

The second layer takes the way-point produced by the first layer as a sub goal. This layer produces a local trajectory which guides the robot toward the way-point while avoiding collisions with obstacles. A ring of short-range sensors is used to implement a reactive navigation algorithm wherein local direction and speed commands are generated in response to near obstacles as the robot seeks the way-point. In a manner analogous to the first layer algorithm, the way-point is used as a desired direction for the robot while sensor inputs are used to infer a direction that allows the robot to avoid obstacles. The simultaneous objectives of sub goal seeking and obstacle avoidance are combined to produce a safe heading for the robot. The rule base for the second layer is of the general form shown below.

If sensor S is fired, Then   the direction indicated by S becomes fully disallowed. ………… (7)

V. RESULT AND DISCUSSION

A final feature of the algorithm is the implementation of a deadlock handling mechanism. The robot enter a situation in which obstacles block a direct path to the final goal and such obstacles are too large for long-range sensors to plan a path around, the fuzzy algorithm presented thus far could result in oscillatory motion that does not result in progress toward the goal. In such situations, the robot needs a strategy breaking the cycle of unproductive decisions. Typically, this is handled with a wall (or contour) following behavior until a safe trajectory is discovered. The infrared sensors in Koala (6-wheeled) robot are used as both long- and short-range detectors by setting their thresholds accordingly. Experimental results are divided into those for static versus dynamic environments. In a static environment, the algorithm determines only reachable way-points. Graphs of sensor readings show that the readings are generally low except when a way-point is close to the vertex of an obstacle. This behavior is interpreted as the algorithm’s ability to avoid obstacles before coming close to them. Further, this behavior represents avoidance of the shortsighted behavior problem associated with a purely reactive fuzzy controller. The algorithm’s behavior in a dynamic environment involves movement of obstacles during the robot’s passage so as to render some way-points unreachable.

VI. CONCLUSION

Finally, in order to demonstrate the effectiveness of the layered algorithm over earlier methods, the Koala robot is programmed (separately) with only reactive direction-based and speed-based fuzzy algorithms. Compared to these algorithms, the layered approach produces improvements in navigation time. Further, it is seen that the layered approach produces a smoother trajectory and avoids obstacles before coming in close proximity to them. This behavior allows wheel velocities to remain roughly constant with respect to one another resulting in less directional oscillation.

FUTURE SCOPE

Coupled with the strengths of fuzzy approaches in simplicity and ease of implementation are the challenges of overcoming local minima. Application of fuzzy logic in mobile robot navigation in 2D environment address the challenges would seem to hold the greatest promise for real world implementation.

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