

*Full Length Research Paper*

# Behavior architecture controller for an autonomous robot navigation in an unknown environment to perform a given task

Jasmine Xavier A.<sup>1\*</sup> and Shantha Selvakumari R.<sup>2</sup>

<sup>1</sup>Jayaraj Annapackiam CSI College of Engineering, Anna University, Chennai, Tamil Nadu India.

<sup>2</sup>Mepco Schlenk Engineering College, Anna University, Chennai, Tamil Nadu India.

Received 5 December, 2014; Accepted 27 January, 2015

The aim of this paper is to carry out navigation task in an unknown environment with high density obstacles using an autonomous mobile robot. Fuzzy logic approach is used for the robot planning because the output varies smoothly as the input changes. If the navigation environment contains one or more obstacles the robot must be able to avoid collisions. The robot uses the obstacle avoidance controller in order to reach the final destination safely without collision with these objects. The robot moves toward the goal and when an obstacle is detected in one of the three sides (front, left, right) the obstacle avoidance behavior is activated to generate the appropriate actions for avoiding these collisions.

**Key words:** Robot navigation, robot exploration, goal seeking.

## INTRODUCTION

There is growing interest in applications of mobile robots. This is due to the fact that the robots are finding their way out of sealed working stations in factories to our homes and to populated places such as museum halls, office buildings, railway stations, department stores and hospitals (Shuzhi and Lewis, 2006). Mobile robots have been the object of many researchers over the last few years in order to improve their operational capabilities of navigation in an unknown environment which consist of the ability of the mobile robot to plan and execute a collision-free motion within its environment. However, this environment may be imprecise, complex and either partially or non-structured (Janglova, 2004). The path

planning problem of a mobile robot can be stated as: given the starting position of the robot, the target location and a description of its surrounding environment, plan a collision-free path between the specified points under satisfying an optimization criterion (Sugihara and Smith, 1997). The path planning in an unknown environment depends on the different sensory systems (cameras, sonar, etc.) which provide a global description of the surrounding environment of the mobile robot; therefore, this description might be associated with imprecision and uncertainty. Thus, to have a suitable path planning scheme, the controller must be robust to the imprecision of sensory measurements. Hence, the need for an

\*Corresponding author. E-mail: [jtony2012@gmail.com](mailto:jtony2012@gmail.com)

Author(s) agree that this article remain permanently open access under the terms of the [Creative Commons Attribution License 4.0 International License](https://creativecommons.org/licenses/by/4.0/)

approach such as fuzzy logic (Ehsan et al., 2011; Beom and Cho, 1995) which can deal with uncertainties is more suitable for this kind of situations. In real-world problem for autonomous mobile robot navigation, it should be capable of sensing its environment, understanding the sensed information to receive the knowledge of its location and surrounding environment, planning a real-time path from a starting position to goal position with hurdle avoidance, and controlling the robot steering angle and its speed to reach the target. Fuzzy Logic is used in the design of possible solutions to perform local navigation, global navigation, path planning, steering control and speed control of a mobile robot. Fuzzy Logic (FL) and Artificial Neural Network (ANN) are used to assist autonomous mobile robot move, learn the environment and reach the desired target (Velappa et al., 2009). Fuzzy logic was used in many works to design robust controllers for the navigation of mobile robots in a cluttered environments and it can solve such complex real world problems within a reasonable accuracy and a low computational complexity, due to their heuristic nature. In addition, genetic algorithms (Seng et al., 1999), neural networks (Kian et al., 2002) and their combinations were developed to construct the fuzzy logic controller automatically. However, the fusion of different behaviors remains to be difficult when they attempt to control the same actuator simultaneously. Many efforts have been devoted to solve the problem of fusion behavior methods. Because of the complexity of the surrounding environment to be characterized or modeled accurately, behavior architecture control applications become important for the mobile robots navigation. It decomposes the navigation system into specific behavior. Behavior architecture modules which are connected directly to sensors and actuators and operate in parallel. Simple behaviors are then combined in order to produce a complex strategy able to pursue the strategic goals while effectively reacting to any contingencies. Therefore, this architecture can act in real-time and has good robustness. Brooks (1986) proposed an architecture that has been applied successfully in mobile robot navigation, but its main drawback is the arbitration technique which allows only the activation of one behavior at one time. In many situations, the activation of two behaviors is required, for example, when the robot is moving toward the target and avoids obstacles at the same time, two behaviors should be combined to fulfill this task (Yung and Ye, 1999). The basic idea in behavior based navigation is to subdivide the navigation task into small easy to manage, program and debug behaviors (simpler well defined actions) that focus on execution of specific subtasks. For example, basic behaviors could be "avoiding obstacles", "goal seeking" or "wall following". This divide and conquer approach has turned out to be a successful approach, for it makes the system modular, which both simplifies the navigation solution as well as offers a possibility to add new behaviors to the system

without causing any major increase in complexity (Brooks, 1989; Saffiotti, 1997). The suggested outputs from each concurrently active behavior are then "blended" together according to some action coordination rule (Fatmi et al., 2006; Ye et al., 2003).

## RELATED WORK

Yung and Ye (1999) presented a new method for behavior based control for mobile robots path planning in unknown environments using fuzzy logic. The main idea of this paper is to incorporate fuzzy logic control with behavior-based control. The basic behaviors are designed based on fuzzy control technique and are integrated and coordinated to form complex robotics system. More behaviors can be added into the system as needed. The output from the target steering behavior and the obstacle avoidance behavior are combined to produce a heading which takes a robot towards its target location while avoiding obstacles. Player/Stage simulation results show that the proposed method can be efficiently applied to robot path planning in complex and unknown environments by fusing multiple behaviors and the fuzzy behaviors made the robot move intelligently and adapt to changes in its environment. Seng et al. (1999) demonstrated a successful way of structuring the navigation task in order to deal with the problem of mobile robot navigation. Issues of individual behavior design and action coordination of the behaviors were addressed using fuzzy logic. The coordination technique employed in this work consists of two layers. A layer of primitive basic behaviors, and the supervision layer which based on the context makes a decision as to which behavior(s) to Fuzzy Logic Based Navigation of Mobile Robots process (activate) rather than processing all behavior(s) and then blending the appropriate ones, as a result time and computational resources are saved. Simulation and experimental studies were done to validate the applicability of the proposed strategy. Yang et al. (2005) proposed an approach which utilizes a hybrid neuro-fuzzy method where the neural network effectively chooses the optimum number of activation rules time for real-time applications. Initially, a classical fuzzy logic controller has been constructed for the path planning problem. The inference engine required 625 if-then rules for its implementation. Then the neural network is implemented to choose the optimum number of the activation rules based on the input crisp values. Simulation experiments were conducted to test the performance of the developed controller and the results proved that the approach to be practical for real time applications. The proposed neuro-fuzzy optimization controller is evaluated subjectively and objectively with other fuzzy approaches and also the processing time is taken into consideration. Samsudin et al. (2011) dealt with the reactive control of an autonomous mobile robot

which should move safely in a crowded unknown environment to reach a desired goal. A successful way of structuring the navigation task in order to deal with the problem is within behavior based navigation approaches. In this study, issues of individual behavior design will be addressed using fuzzy logic approach. Simulation results show that the designed fuzzy controllers achieve effectively any movement control of the robot from its current position to its end motion without any collision. Wang and Liu (2008) proposed a new behavior-based fuzzy control method for mobile robot navigation. This method takes angular velocities of driving wheels as outputs of different behaviors. Fuzzy logic is used to implement the specific behaviors. In order to reduce the number of input variables, we introduced a limited number of intermediate variables to guarantee the consistency and completeness of the fuzzy rule bases. To verify the correctness and effectiveness of the proposed approach, simulation and experiments were performed. Seraji and Howard (2002) presented a simple fuzzy logic controller which involves searching target and path planning with obstacle avoidance. In this contest, fuzzy logic controllers are constructed for target searching behavior and obstacle avoidance behavior based on the distance and angle between the robot and the target as inputs for the first behavior and the distance between the robot and the nearest obstacle for the second behavior; then a third fusion behavior is developed to combine the outputs of the two behaviors to compute the speed of the mobile robot in order to fulfill its task properly. Simulation results show that the proposed approach is efficient and can be applied to the mobile robots moving in unknown environments. Selekwia et al. (2005) proposed navigation and obstacle avoidance in an unknown environment using hybrid neural network with fuzzy logic controller. The overall system is termed as Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS combines the benefits of fuzzy logic and neural networks for the purpose of achieving robotic navigation task. Abdessemed et al. (2004) presented a Mamdani type minimum rule base fuzzy logic system which has been used successfully in a control system for robot hurdles avoidance in cluttered environment. The fuzzy logic will collect the sonar measurement data as inputs, and select an action for the robot so that it can navigate in the environment successfully.

Mobile robots have expected a substantial concentration from early research community, up to this instant. Today a fully automated robot is expected to travel, detect objects and explore any unknown environments. One such interest is focused on the predicament of generating a map for a functioning environment depiction for navigational tasks. A robot explores while travelling on a trajectory, with its sensors it senses the obstacles and generates a map. The most common sensors used are sonar and laser scanners, which detect the distance of an obstacle within the range

of the sensors by transmitting out signal and compute the time till the resonance of the signal income. The ultrasound rangefinders have a very wide possibility of exploitation due to their ease of functioning, low cost and modest realization. In the majority of circumstance the signal will bounce against the nearby obstacle in the course of the sensor and as a result the calculated distance will be the distance to the nearby obstacle. But however, there are some occasions where there occur measurement failures, and as a result the calculated distance becomes flawed. These measurement failures may occur due to the uncertainties provided by the range measuring sensors. These uncertainties are origin by the characteristics of air such as its temperature, humidity, turbulence and pressure.

One such ambiguity results from the promulgation of the ultrasonic signal to the space in the form of a cone with an axis in the scanning course. So the exact angular position of the object reflecting the echo might not be determined, because it may occur somewhere along the arc with the radius of the measured distance. A further cause of ambiguity is a experience of numerous reflections, that occurs in the case that the incidence angle of signal to the obstacle is larger than a so called critical angle, which is strongly reliant on the exterior distinctiveness. In this occurrence the reflection of the signal is mainly specular and the sensor may perhaps receive the ultrasonic beam after numerous reflections, what is called a elongated reading, or it may even get lost. Consequently, to return a momentous range reading, the angle of incidence on the object exterior has to be lesser than the critical angle.

Steering and obstacle evading are very significant issues for the doing well use of a sovereign mobile robot. Computing the configuration succession, allow the robot to move from one location to a further location. When the surroundings of the robot are obstacle free, the predicament becomes not as much of complex to handle. But as the surroundings becomes a complex, movement planning need much more effective to allow the robot to move between its in progress and closing configurations without any collision with the surroundings. A flourishing approach of configuring the steering assignment to deal with the dilemma is within behavior based navigation approaches.

The fundamental scheme in behavior based steering is to subdivide the navigation task into diminutive simple to supervise, course and sort out behaviors that focus on implementation of explicit sub schemes. For illustration, fundamental behaviors could be obstacle avoiding, target seeking, or wall following. This split and triumph over approach has turned out to be a flourishing approach, for it makes the scheme modular, which both make simpler the steering way out as well as tender a prospect to insert new behaviors to the system without causing any major increase in complexity.

The intention of this dissertation is to be evidence for

how to conduct an autonomous mobile robot in unfamiliar surroundings by means of fuzzy logic approach and to build map based on the range readings obtained from the sensors. Fuzzy logic control (FLC) is an appealing contrivance to be useful to the dilemma of conduit arrangement given that the output varies efficiently as the input adjusts. In this exertion, we will discuss a fuzzy conduit arrangement controller design based on connoisseur understanding and information that was applied to a mobile robot. The fuzzy inference system is based on a person driver reminiscent of interpretation in a indoor surroundings that is vacant or surround obstacles.

The paper is structured as follows: At first, the sculpt of the mobile robot is presented and the essential background of fuzzy logic method and a epigrammatic of fuzzy behavior based steering is presented. The proposed organizers, the map building algorithms are introduced and elucidated. Simulation results for illustration of movement of the robot in unknown surroundings are demonstrated.

## DESIGN OF FUZZY BEHAVIOR BASED NAVIGATION METHOD

### Mobile robot kinematics

In this exploration, a differentially ambitious mobile robot is used; its kinematic illustration is show in the Figure 1. The kinematic model of the mobile robot has two rear driving wheels and a passive front wheel. The inputs of the scheme are the steering angle  $\alpha$  of the front wheel and the linear velocity  $V_R$ . The outputs are the coordinates of the robot ( $X_R$ ,  $Y_R$  and  $\theta_R$ ). In ideal sticking together circumstances, this kinematic model can be described by the following equations:

$$X_R = V_R * \cos(\theta_R) \quad (1)$$

$$Y_R = V_R * \sin(\theta_R) \quad (2)$$

$$\theta_R = V_R * \text{tg}(\alpha) / l \quad (3)$$

Where  $X_R$ ,  $Y_R$  are the position coordinates,  $\theta_S$  angle error between the robot axis and goal vector and  $\theta_R$  is the orientation angle of the robot.  $l$  is the robot length. In our work, we suppose that the simulated mobile robot is able to detect the coordinates of the final goal and it is equipped by sensors for perceiving its environment.

### Fuzzy logic approach

The premise of fuzzy logic scheme is motivated by the significant human ability to rationale with perception based information. Rule based fuzzy logic afford a proper methodology for linguistic rules ensuing from interpretation and decision making with ambiguous and indefinite information. The building block illustration of a fuzzy control scheme is shown in Figure 2. The fuzzy controller is composed of fuzzification interface, a rule base, an interface mechanism. The fuzzification interface renovates the actual controller inputs into information so as to the inference mechanism can straightforwardly exercise to make active and relate rules. A rule-base has a set of If-Then rules which enclose a fuzzy logic quantification of the connoisseur's linguistic depiction of how to

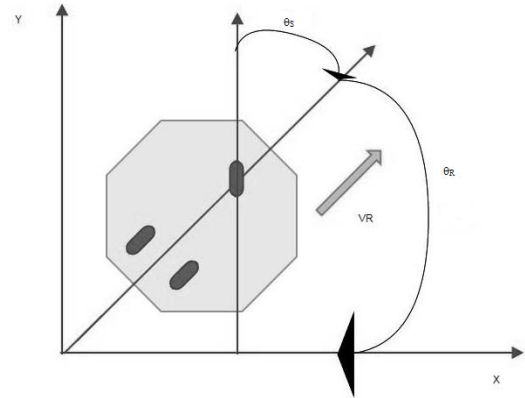


Figure 1. Mobile robot kinematics.

accomplish superior control. An inference mechanism emulates the connoisseur's decision making in interpreting and concern understanding about how preeminent to direct the plant. defuzzification interface renovate the conclusions of the inference mechanism into actual inputs for steering the course. Mamdani and Takagi-Sugeno model are two popular models used mostly in fuzzy logic control. In this paper we use zero order Takagi-Sugeno model owing to its simplicity and effectiveness to the course control.

### Design of robot steering and velocity control

The motion control variables of the mobile robot are the angular velocity of the front wheel and the velocity of the rear wheels. The angular velocity is represented by  $\theta_R$ . The vehicle velocity is determined by the rear wheels speed which is denoted by  $V_R$ . The position of the vehicle is denoted by ( $X_R$ ,  $Y_R$ ).

The left steering angle is represented by a three-variable linguistic fuzzy input membership set  $\{S, LO1, LO2\}$  which define the distance of the obstacles in three different levels from farthest to the closet respectively, the obstacle distances are estimated from the ultrasound sensor range readings, and the output membership set  $\{ST, L1, L2\}$  which define the steering actions to the left of the vehicle in the different levels from straight steering to intense left turning actions respectively.

Similarly the right steering angle is represented by a three-variable linguistic fuzzy input membership set  $\{S, RO1, RO2\}$  which define the distance of the obstacles in three different levels from farthest to the closet respectively, and the output membership set  $\{ST, R1, R2\}$  which define the steering actions to the right of the vehicle in the different levels from straight steering to intense left turning actions respectively. The rule base of the steering behavior is summarized in Table 1.

Similarly the motor speed of the rear wheel is represented by a five-variable linguistic fuzzy input membership set  $\{D1, D2, D3, D4, D5\}$ , defines the five different levels of obstacle distance from the front end of the mobile robot from very near to the farthest position respectively and the output membership  $\{V1, V2, V3, V4, V5\}$  which define the velocity actions such as too slow, slow, medium, fast, fastest most respectively.

### Design of goal seeking behavior

The mission of the robot is to arrive at a preferred position in the surroundings called a goal. This goal seeking behavior is anticipated to line up the robot's cranium with the course of the goal

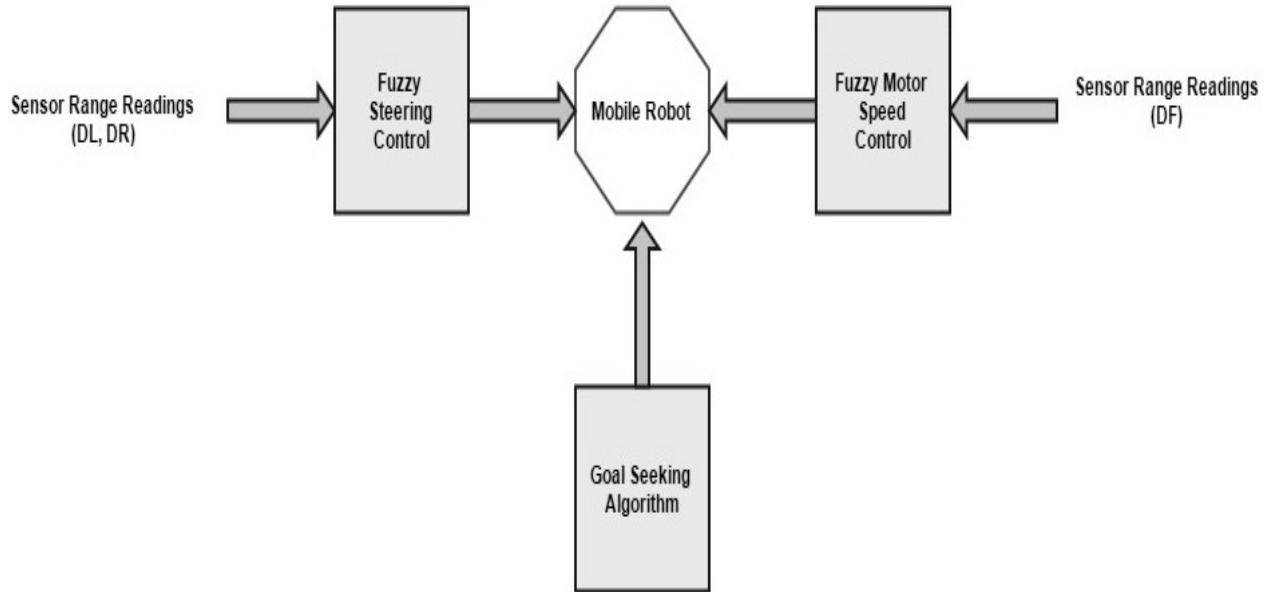


Figure 2. Block Diagram of the proposed scheme.

Table 1. Fuzzy rule set.

| Fuzzy rule base for steering control   | Fuzzy rule base for motor control  |
|--|--|
| 1. If (input1 is LO2) then (output1 is L2)<br>2. If (input1 is LO1) then (output1 is L1)<br>3. If (input1 is S) then (output1 is ST) | 1. If (input1 is D1) then (output1 is V1)<br>2. If (input1 is D2) then (output1 is V2)<br>3. If (input1 is D3) then (output1 is V3)<br>4. If (input1 is D4) then (output1 is V4) |
| 1. If (input1 is RO2) then (output1 is R2)<br>2. If (input1 is RO2) then (output1 is R1)<br>3. If (input1 is S) then (output1 is ST) | 5. If (input1 is D5) then (output1 is V5)  |

coordinates. The calculation module compares the actual robot coordinates with the coordinates of the target using mathematical equations. The outputs are the angle noted  $\theta_D$  and the distance between the robot and the goal (position error) noted  $D_{RG}$ . The angle value is compared with the orientation of the robot delivered by the odometry module in order to compute the angle error  $\theta_{ER}$  between the robot axis and the goal vector. Prearranged a mobile robot, it must be capable to engender a course between two specific position, the start nodule and the target nodule. The course ought to be free of collision and be required to persuade convinced optimization criterion i.e. least time consuming course. The only information offered to the robot is it's in progress location and the location of the goal in the grid map. The robot has to constantly be in motion from the in progress position until it reaches the goal by avoiding the obstacles detected on course. Occupancy grids are used for the representation of the environment.

At this juncture each cell in the grid encloses information concerning its circumstances, which is premeditated depending on the probability of occupancy of that particular cell. Consequently a cell which is engaged by an obstacle will cover a very high probability of occupancy cost returned by the sensor, which makes it engaged for the robot to pass through. Frontier based heuristic exploration algorithm is the chief province of the dilemma. It is

helpful in situations wherever no preceding preparation is viable and all decisions are taken at instantaneous.

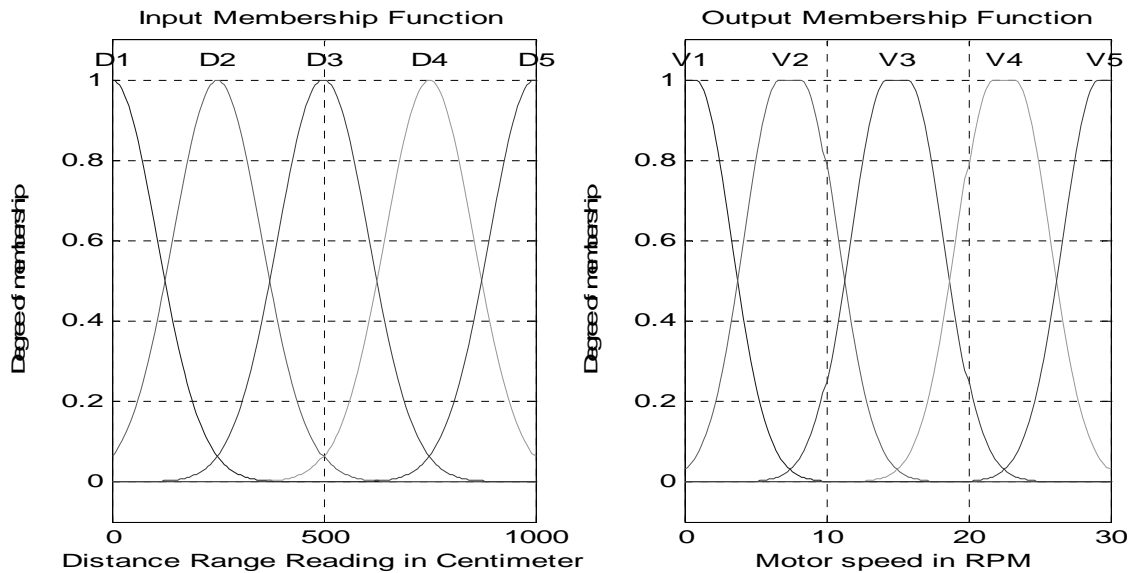
To begin with the robot executes a bursting surrounding look into of its surroundings and updates the occupancy cost  $G_O$  of its four neighboring cells, one in each course: top, right, bottom and left. These four cells sensed on each scan are termed as the cells in the in progress sensing area. A frontier cell is a cell explored by the robot which is having at least one unexplored cell as its neighboring cell. After each scanning operation, the newly detected frontier cells are assigned heuristic cost value known as Goal Seeking Index  $G_{Si}(X_R, Y_R)$ . The cost of moving to a cell  $(X_R, Y_R)$  is found as the product of its occupancy cost  $G_O$  and the distance of the cell  $(X_R, Y_R)$  from the in progress position of the robot. Calculating the cost based on occupancy value is explained well in the GSI for each frontier cell is found out with the help of Equation (4):

$$G_{Si}(X_R, Y_R) = ((D_{MAXIMUM} - D_{((X,Y),TARGET)}) - C_{((X,Y),CURRENT)}) \quad (4)$$

Where  $D_{MAXIMUM}$  is the principal distance probable amid any cell in the grid and the goal location,  $D_{((X,Y),TARGET)}$  is the distance amid the given frontier cell  $(X_R, Y_R)$  and the goal cell, and  $C_{((X,Y),CURRENT)}$  is product of the occupancy cost ( $G_O$ ) of the frontier cell  $(X_R, Y_R)$  and its distance from the current location of the robot.

**Table 2.** Simulation parameters.

| Specification                 | Description                   |
|-------------------------------|-------------------------------|
| Operating System              | Windows Seven                 |
| Simulation Tool               | MATLAB 2009                   |
| Number of Robots              | 1                             |
| Simulation Area               | 50m x 50m                     |
| No of wheels                  | 3 (2 Rear + 1 front steering) |
| Minimum – Maximum Motor Speed | 0-30 RPM                      |



**Figure 3.** Input and output membership function for Motor speed control.

**RESULTS AND DISCUSSION**

For the proposed scheme, simulation has been done with MATLAB. The simulation parameters are described in Table 2. Figure 3 shows a five-variable linguistic fuzzy input membership set {D1, D2, D3, D4, D5}, defines the five different levels of obstacle distance from the front end of the mobile robot from very near to the farthest position respectively and the output membership {V1, V2, V3, V4, V5} which define the velocity actions such as too slow, slow, medium, fast, fastest most respectively. Figure 4 shows the left steering angle which is represented by a three-variable linguistic fuzzy input membership set {S, LO1, LO2} which define the distance of the obstacles in three different levels from farthest to the closet respectively, the obstacle distances are estimated from the ultrasound sensor range readings, and the output membership set {ST, L1, L2} which define the steering actions to the left of the vehicle in the different levels from straight steering to intense left turning actions respectively. Similarly the right steering

angle is represented by a three-variable linguistic fuzzy input membership set {S, RO1, RO2} which define the distance of the obstacles in three different levels from farthest to the closet respectively, and the output membership set {ST, R1, R2} which define the steering actions to the right of the vehicle in the different levels from straight steering to intense left turning actions respectively. Figure 5 shows the robot steering control achieved in turn angle with respect to the distance of the obstacle sensed in the left and right of the robot. Figure 6 shows the robot speed control achieved in rotations per minute with respect to the obstacle distance sensed by the front sensor range readings. Figures 7, 8 and 9 shows the robot goal seeking in a MATLAB simulated environment with a high obstacle density similar to a maze like environment. Here, the robot is supposed to move from the start point  $(X_i, Y_i) = (45, 45)$  to the goal  $(X_T, Y_T) = (5, 5)$  in two different environments. The initial orientation of the robot is  $\theta_m = \pi/2$  and there are many obstacles in the environment. The obtained results show the efficiency of the proposed control method. In all the

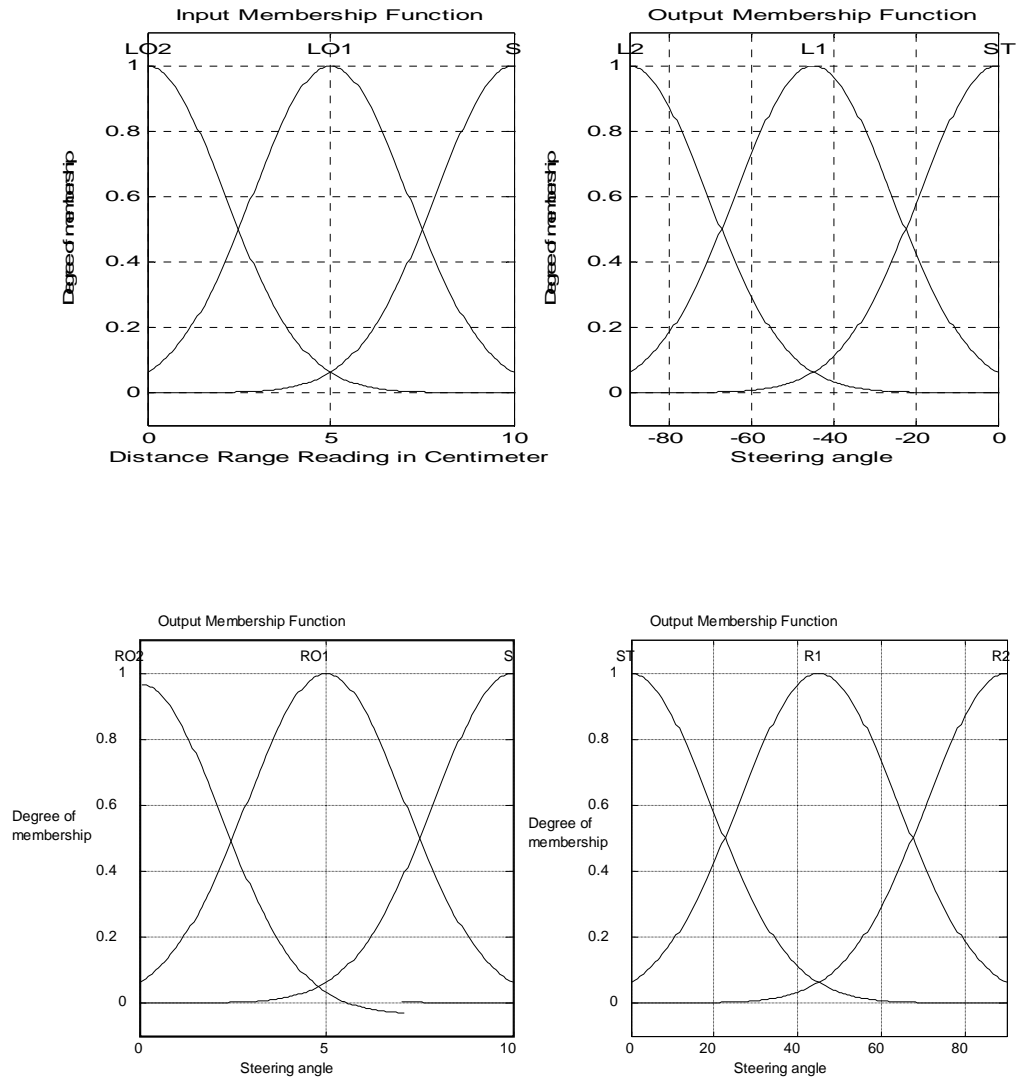


Figure 4. Input and output membership function for motor steering control.

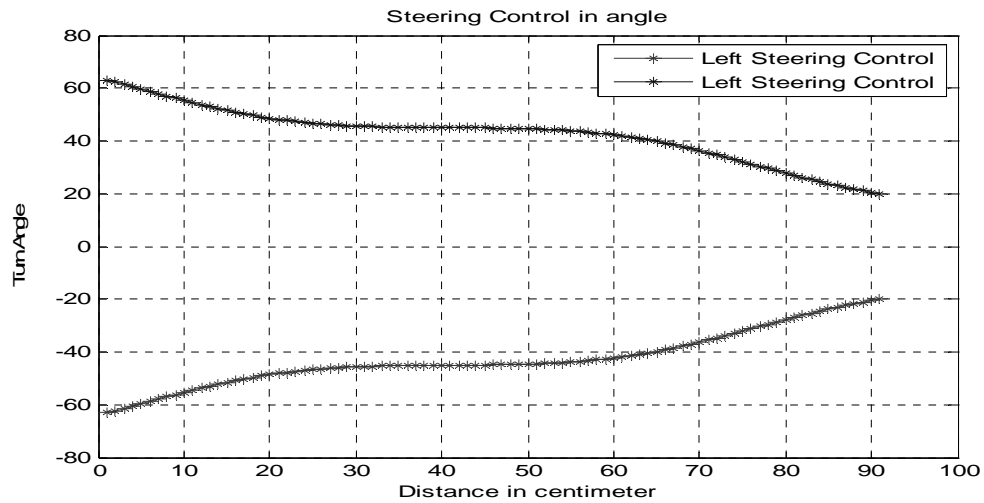


Figure 5. Robot steering control distance vs. turn angle.

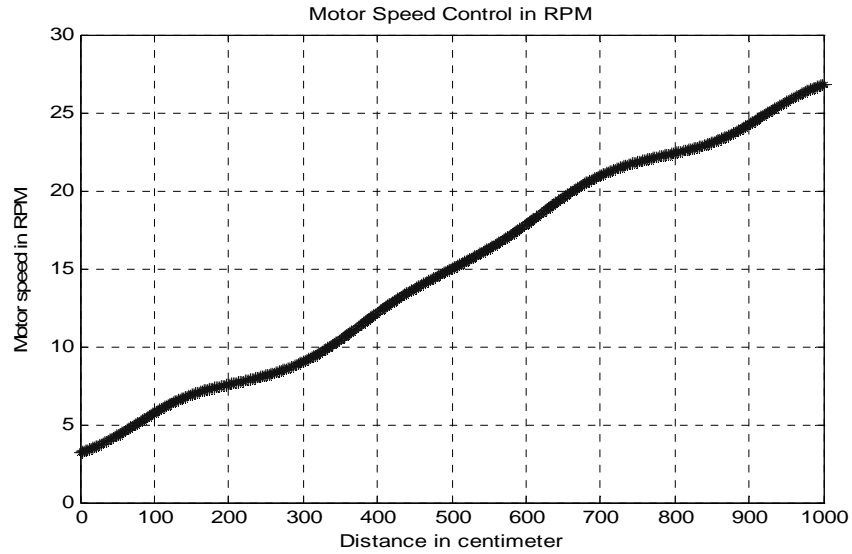


Figure 6. Robot speed control distance vs. motor speed in RPM.

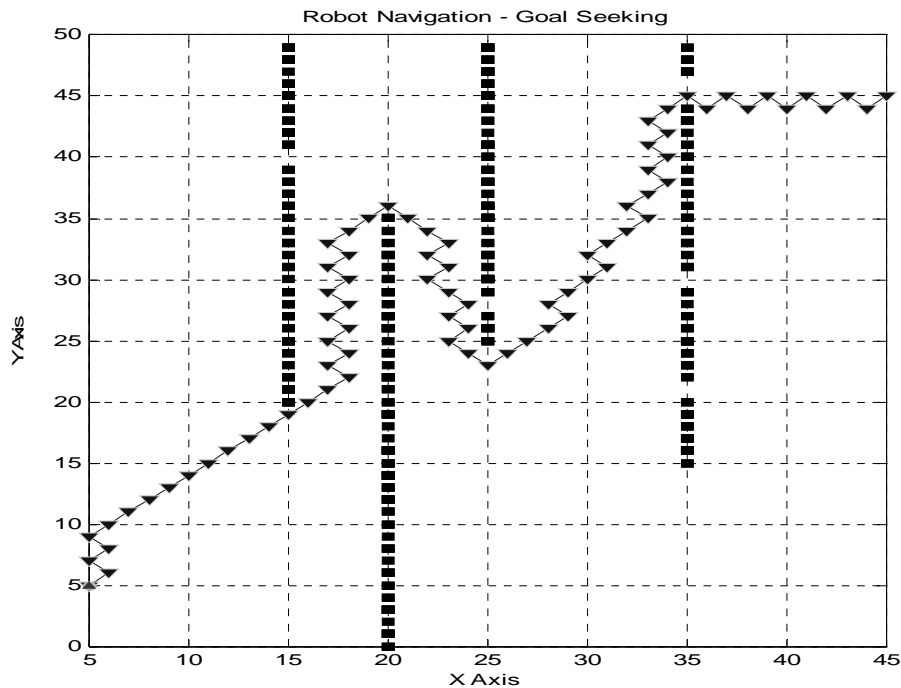


Figure 7. Robot goal seeking in Environment 1.

different configuration of the environment, the robot is able to reach the goal point.

**CONCLUSION**

This work presented a method that can be efficiently

used to design behaviors based steering scheme. An uncomplicated harmonization scheme is used to toggle between steering procedures according to outputs of apiece manners. The outcome attained illustrates the effectiveness of the proposed control scheme. In every scenario, the robot is capable to arrive at the goal in diverse configurations of the surroundings by avoiding



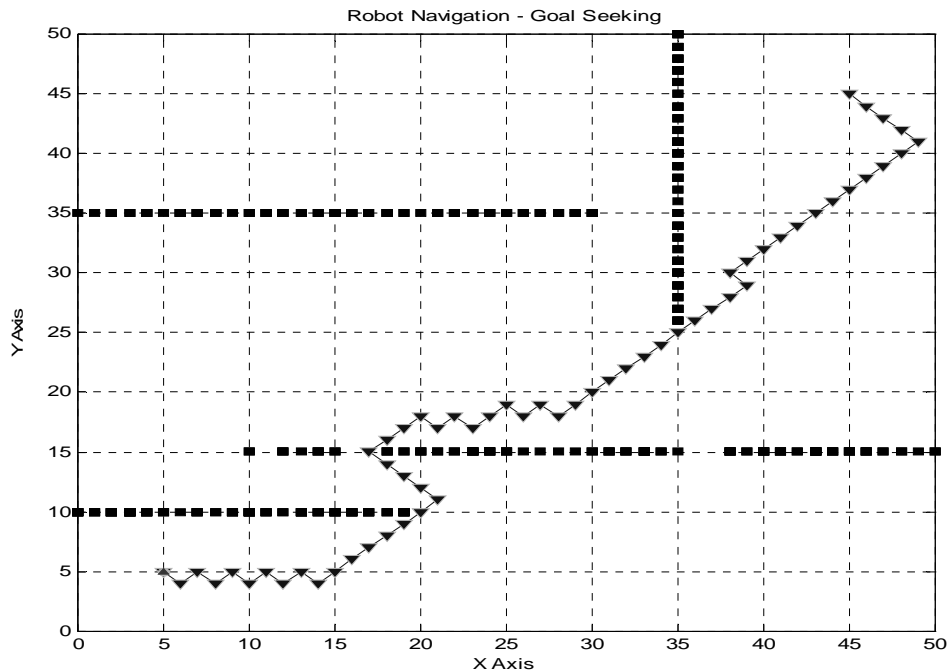


Figure 8. Robot goal seeking in Environment 2.

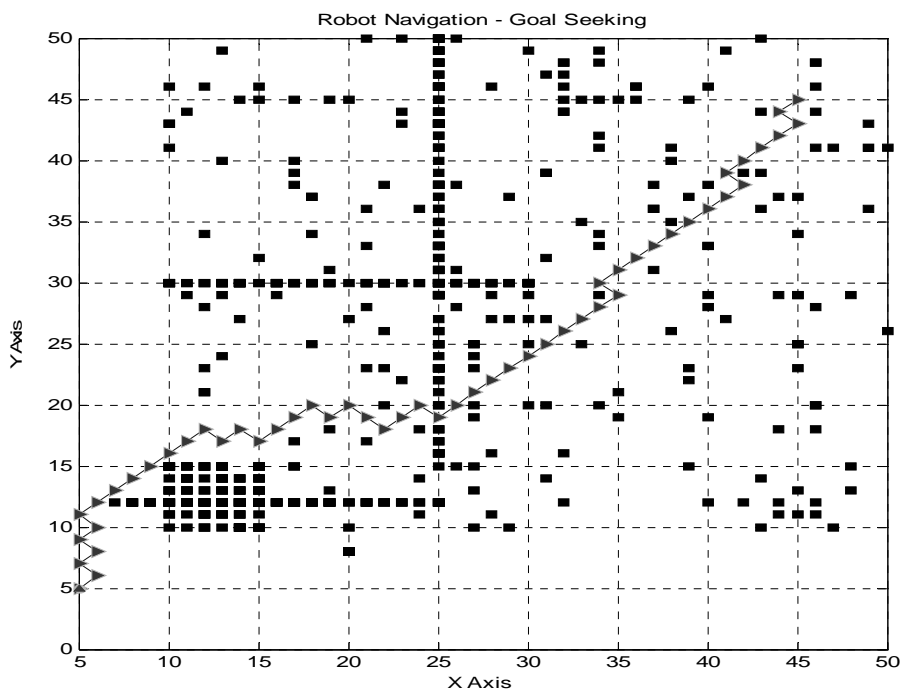


Figure 9. Robot goal seeking in Environment 3.

obstacles. It is of an immense significance to highlight on the attained efficiency of the robot activities. In prospect the attention will be certain to the development of an

inclusive steering scheme counting other behaviors like wall following and avoiding moving obstacles. In future works, the interest will be given to moving obstacles.

## Conflict of Interest

The authors have not declared any conflict of interest.

## REFERENCES

- Abdessemed F, Benmahammed K, Monacelli E (2004). A fuzzy based reactive controller for a non-holonomic mobile robot. *Robotics and Autonomous Systems*. 47(1):31–46.
- Beom HR, Cho HS (1995). A sensor-based navigation for a mobile robot using fuzzy Logic and Reinforcement Learning. *IEEE Tran. Syst. Man. Cyber.* 25(3):464-477.
- Brooks RA (1989). A Robot that Walks; Emergent Behavior from a Carefully Evolved Network. *IEEE International Conference on Robotics and Automation*. Scottsdale, AZ. pp. 292–296.
- Brooks RA (1986). A Robust Layered Control System for a Mobile Robot. *IEEE J. Robotics Autom.* RA-2(1):14–23.
- Ehsan H, Maani GJ, Navid GJ (2011). Model based PI-fuzzy control of four-wheeled omni-directional mobile robots. *Robot. Autom. Syst.* 59(11):930-942.
- Fatmi AS, Yahmedi Al, Khriji L, Masmoudi N (2006). A Fuzzy Logic based Navigation of a Mobile robot. *World academy Sci. Eng. Technol.* 22:169-174.
- Janglova D (2004). Neural networks in mobile robot motion. *Int. J. Adv. Robot. Syst.* 1(1):15-22.
- Kian HL, Wee KL, Jr, Ang MH (2002). Integrated planning and control of mobile robot with self-organizing neural network. *Proceeding of 18th International Conference on Robotics and Automation (ICRA '02)*. May 11-15, 4:3870-3875.
- Saffiotti A (1997). The uses of fuzzy logic for autonomous robot navigation. *Soft Comput.* 1(4):180-197.
- Samsudin KF, Ahmad A, Mashohor S (2011). A highly interpretable fuzzy rule base using ordinal structure for obstacle avoidance of mobile robot. *Appl. Soft Computing J.* 11(2):1631–1637.
- Selekwa MF, Damion D, Collins Jr. EG (2005). Implementation of multi-valued fuzzy behavior control for robot navigation in cluttered environments. *Proceedings of the 2005 IEEE International Conference on Robotics and Automation, Barcelona, Spain*. pp. 3699-3706.
- Seng TL, Khalid MB, Yusof R (1999). Tuning a Neuro-Fuzzy Controller by Genetic Algorithm. *IEEE Trans. Syst. Man. Cybernetics* 29(2):226-236.
- Seraji H, Howard A (2002). Behavior - based robot navigation on challenging Terrain: A Fuzzy Logic Approach. *IEEE Trans. Rob. Autom.* 18(3):308-321.
- Shuzhi SG, Lewis FL (2006). *Autonomous Mobile Robots, Sensing, Control, Decision, Making and Applications*, CRC, Taylor and Francis Group.
- Sugihara K, Smith J (1997). Genetic algorithms for adaptive motion planning of an autonomous mobile robot. *Proceedings of the IEEE International Symposium on Computational Intelligence in Robotics and Automation*. pp.138-146.
- Velappa G, Soh CY, Jefry Ng (2009). Fuzzy and neural controllers for acute obstacle avoidance in mobile robot navigation. *IEEE/ASME International Conference on Advanced Intelligent Mechatronics Suntec Convention and Exhibition Center*. pp.1236-1241.
- Wang M, Liu JNK (2008). Fuzzy logic-based real-time robot navigation in unknown environment with dead ends. *Robotics Autonomous Syst.* 56(7):625–643.
- Yang SX, Moallem M, Patel RV (2005). A layered goal-oriented fuzzy motion planning strategy for mobile robot navigation. *IEEE transactions on systems, man, and cybernetics—part b: cybernetics*. 35(6):1214-1224.
- Ye CN, Yung HC, Wang D (2003). A fuzzy controller with supervised learning assisted reinforcement learning algorithm for obstacle avoidance. *IEEE Trans. Syst. Man. Cybern. B.* 33(1):17-27.
- Yung NHC, Ye C (1999). An intelligent mobile vehicle navigator based on fuzzy logic and reinforcement learning. *IEEE Trans. Syst. Man. Cybern.* 29(2):314-321.