Original Article

Print ISSN: 2321-6379
Online ISSN: 2321-595X
DOI: 10.17354/ijssI/2017/35

A New Global Fuzzy Path Planning and Obstacle Avoidance Scheme for Mobile Robots

Vahid Meigoli[1], Mojtaba Hadi Barhaghtalab[1]*, S K Y Nikravesh[2], H A Talebi[2]

[1]Department of Electrical Engineering, School of Engineering, Persian Gulf University, Bushehr, Iran, [2]Department of Electrical Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

Abstract

In this paper, a new global path planning and obstacle avoidance scheme for mobile robot is proposed. The key to avoiding the obstacle is to fuzzify them and construct a fuzzy graph from the environment. Then, based on human performance a set of fuzzy rules is defined for robot navigation using these fuzzy sets and sub-optimal paths to the goal are generated. A fuzzy rule is defined for avoiding each obstacle and a new obstacle can be added to the fuzzy graph at any time. Hence, the fuzzy rules can be updated with the changes in the environment. Unlike other fuzzy path planning approaches, this scheme does not fall into local minima. Simulation results are also presented to evaluate the performance of the new scheme.

Key words: Mobile robot, obstacle avoidance, Fuzzy control, Fuzzy obstacle, Fuzzy graph, Global path planning

INTRODUCTION

Recently, there has been a great deal of activity on motion planning of mobile robots (MR). Most of them, however, use the local environment for reducing the computational efforts. The artificial potential field [1], behavior based fuzzy control [2] and wall following [3] are few to name in this category known as local path planning (LPP). There have also been a few global path planning schemes such as genetic algorithm [4], graphs (of visibility [5], of tangents [6]) and optimal control [7].

The main advantages of LPP approaches are the feasibility of their real-time implementation and their ability for navigation in an unknown environment. However, they suffer from local minima, limit cycles, and instability problems [3,8]. In GPP approaches, global convergence and optimal path [9], but it also suffers from the problems such as extensive computation and the requirement of a priori knowledge about the environment [9].

Access this article online

IJSS

www.ijss-sn.com

Month of Submission : 06-2017
Month of Peer Review : 06-2017
Month of Acceptance : 07-2017
Month of Publishing : 07-2017

Fuzzy logic control (FLC) is often used in conjunction with other algorithms [3-4]. The few researches that used solely FLC for path planning considered LPP approaches [2,10].

The main reason for not using FLC in GPP approaches is that FLC is often realized by a few rules and that is not sufficient for acting with all environment data. The other reason is that the inputs of FLC are often considered as a set of one-dimensional linguistic variables, whereas the robot environment is N dimensional (2 or 3) and expressing the N dimensional data with several one-dimensional variables requires more relations (more rules in FLC).

The approach presented in this paper is a global fuzzy logic path planner. The aforementioned difficulties can be overcome by adapting the number of rules with the complexity of the environment. Moreover, the inputs to FLC are not divided to multiple one-dimensional variables.

We studied the human senses of obstacles, goals, free paths and human behaviors in path planning such as goal seeking, obstacle avoidance, and moving between obstacles. Then, these human senses are used for defining the fuzzy sets and those behaviors are used in obtaining the fuzzy rules.

This paper is organized as follows: In Section 2, the concepts of fuzzy obstacles and fuzzy goal are illustrated. A fuzzy description of the environment called fuzzy graph is generated in Section 3. In Section 4, the new

Corresponding Author: Mojtaba Hadi Barhaghtalab, Department of Electrical Engineering, School of Engineering, Persian Gulf University, Bushehr 7516913798, Iran. E-mail: mh.barhaghtalab@gmail.com

approach is proposed and the fuzzy rules are defined. The simulation results are presented in Section 5 followed by the conclusions in Section 6.

FUZZY OBSTACLES

In this section, the human sense of obstacles and his behavior in obstacle avoidance is explained. Then by considering this sense, the fuzzy sets called "fuzzy obstacles" are defined. Let us proceed with an example.

Consider a driver driving in a narrow alley. The driver tries to be away from edges of the alley. The driver pays more attention to approaching edges. Although the car does not hit the edges of the alley when it is 10cm or 1m away from them, a criterion such as "danger" differs in two cases. In other words, although the region of obstacles presence (here the alley edges) is their boundaries, the degree of their importance decreases outside of their boundaries. Here, the fuzzy obstacles can be defined as the fuzzy sets of points at which the obstacles are important.

Note: It is assumed that the robot dimensions are added to obstacles' dimensions. Hence the robot is considered as a single point.

Definition 1. Consider an obstacle that can be expressed as a subset in $R^2 (Ob \subset R^2)$. A fuzzy version of this subset can be defined. We call this fuzzy set "*fuzzy obstacle*". The value of membership function is equal to one for the points in the obstacle boundary and it decays as we move away from the obstacle. Specifically if the inner points of an obstacle are given by $g_{ob}(x,y) \leq 0$, the fuzzy membership function (FMF) of the fuzzy obstacle by:

$$\mu_{Ob}(x,y) = \begin{cases} 1 & , g_{Ob}(x,y) \leq 0 \\ f\left(g_{Ob}(x,y)/\sigma\right) & , g_{Ob}(x,y) > 0 \end{cases} \tag{1}$$

Where σ is called "*obstacle width*" and *f* is the "*reference function*" defined bellow:

Definition 2. The "*Reference function f* " is a continuous non-increasing function from R^+ to [0,1] with boundary condition $f(0) = 1$.

Membership Function of Convex Fuzzy Obstacles

Figure 1 shows a convex obstacle and point $\vec{P}$ outside of it. Let "r" be the distance between $\vec{P}$ and the obstacle, and $\hat{\alpha}_r$ be the outward unit vector normal to the obstacle. The FMF of fuzzy obstacle can be given by

$$\mu_{Ob}(p) = \begin{cases} 1 & , P \text{ Inside } Ob \\ f(r/\sigma) & , P \text{ Outside } Ob \end{cases} \tag{2}$$

The gradient of $\mu_{ob}(x,y)$ can be obtained as

$$\vec{\nabla}\mu_{Ob}(p) = \begin{cases} 0 & , P \text{ Inside } Ob. \\ \dfrac{df(r/\sigma)}{dr}\hat{\alpha}_r & , P \text{ Outside } Ob. \end{cases} \tag{3}$$

Note: In case of "*concave obstacles*" there are some points in front of two sides of the obstacle. Hence, concave obstacles can be considered as several convex sub obstacles. Consequently, their membership functions can be multivalued functions.

As an example, the FMF of a polygon obstacle with vertices positioned at (3,2), (5,4), (6,3), (4,2) can be selected as shown in Figure 2.

Triangular Fuzzy Obstacle Membership Function

Triangular FMF is often used in fuzzy control because of its simplicity and effectiveness. The triangular reference function defined here will be used in the next sections

$$f(r) = \begin{cases} 1 - r & , 0 \leq r \leq 1 \\ 0 & , \text{Other Wise} \end{cases} \tag{4}$$

When there are several obstacles in environment, the curves formed by connection of the membership functions of these obstacles are good candidates for robot motion. These curves are often formed when some reference

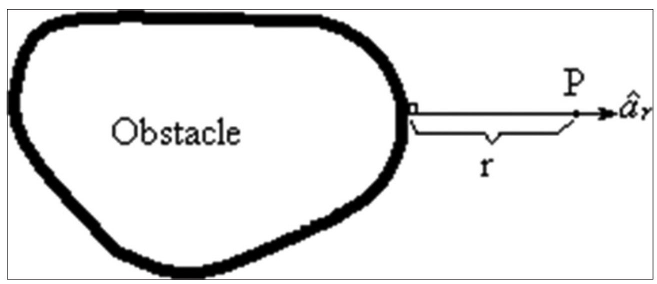

Figure 1: A convex obstacle

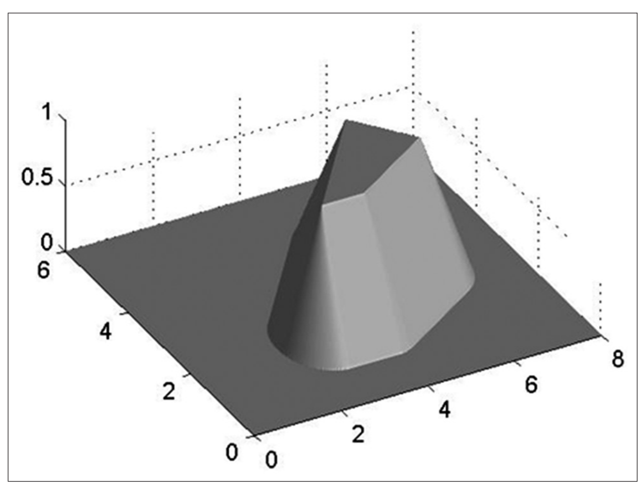

Figure 2: FMF of a polygon

functions such as $f(r)=\exp(-r)$ are used, but they are not formed in some cases when triangular FMFs are used, since triangular FMFs are equal to zero in many points. To solve this problem, the so called generalized obstacle surfaces are defined as

Definition 3. "*Generalized obstacle surface*" is defined as

$$Ob^G(\vec{P})=\begin{cases}1-r/\sigma & ,\vec{P}\ \textit{Outside Obstacle}\\ 1 & ,\vec{P}\ \textit{Inside Obstacle}\end{cases} \tag{5}$$

This function can also take negative values. In this case triangular fuzzy obstacle membership can be given by:

$$Ob(\vec{P})=Ob^G(\vec{P}).u(Ob^G(\vec{P})) \tag{6}$$

Where "u" is the unit step function. Now, the obstacle gradient is defined as the gradient of the generalized obstacle surface:

$$\nabla Ob(\vec{P})=\begin{cases}-\frac{1}{\sigma}\hat{\alpha}_r & ,\vec{P}\ \textit{Outside Obstacle}\\ 0 & ,\vec{P}\ \textit{Inside Obstacle}\end{cases} \tag{7}$$

Fuzzy Goal

A fuzzy set called "fuzzy goal" is a measure of closeness of the robot to the goal. The degree of membership of the points increases as they approach the goal. Naturally the goal seeking behavior is considered by moving in the direction of the gradient of the membership functions of the fuzzy goal.

Definition 4. The "*Fuzzy goal*" can be defined as a fuzzy set in R^2 with cone shape FMF as

$$Goal(\vec{P})=(1-r/\sigma)u(1-r/\sigma) \quad ,r=\left|\vec{P}-\vec{P}_G\right| \tag{8}$$

Definition 5. The "*Generalized goal surface*" and the "*goal gradient*" are defined as

$$Goal^G(\vec{P})=1-r/\sigma \quad ,r=\left|\vec{P}-\vec{P}_G\right| \tag{9}$$

$$\nabla Goal(\vec{P})=\frac{1}{\sigma}\hat{n}_g \quad ,\hat{n}_g=\frac{\vec{P}_G-\vec{P}}{\left|\vec{P}_G-\vec{P}\right|} \tag{10}$$

FUZZY GRAPH

In this section, the human sense of free paths and his/her behavior in goal seeking in a cluttered environment is studied. The following example is used for understanding these concepts.

In Figure 3, an environment is shown with three obstacles Ob_1, Ob_2, Ob_3, a starting point and a goal. The arrows shown in this figure specify the paths that one might consider to reach the goal. These arrows do not show any distinguished curves but they make a sense of directions to move, they are fuzzy concepts.

These arrows specify a directed graph of the environment that each edge is not a directed curve but is a set of directed curves, and each node is not a point but is a set of points. Naturally all curves in one edge do not have similar desirability. For instance, the tangent curves to the obstacles' surfaces have less desirability than the middle curves. Hence, each edge of this graph can be defined as a fuzzy set of points.

Definition 6. The "*Fuzzy graph*" is a graph that each edge and node of it is defined as a fuzzy set of points.

An indoor environment is shown in Figure 4 where three convex obstacles and a goal point are surrounded by a wall. The wall is a concave obstacle and can be considered as five convex sub obstacles. Figure 5 shows an upper view

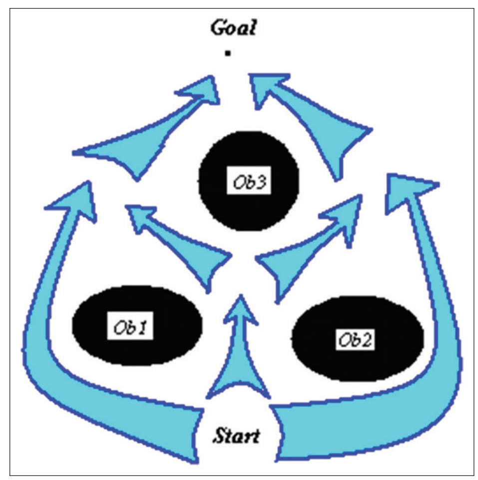

Figure 3: The concept of fuzzy graph

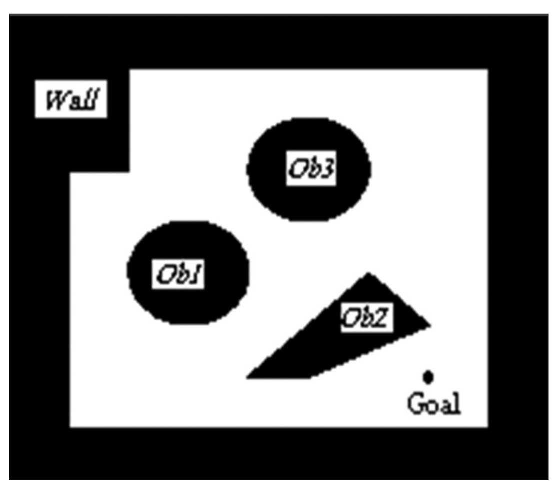

Figure 4: An indoor environment

of the generalized obstacles and the goal surfaces. The edges formed by these surfaces make a crisp graph of the environment, but for making a continuous and smooth control law, a wider graph is needed as shown in Figure 6.

Now, the crisp edge formed between the two surfaces (goal or obstacle surface) is defined.

Definition 7. The "*crisp edge between the ith and the jth surfaces*" is the set of points at which these surfaces have equal values and both have values greater than or equal to those of other surfaces, namely

$$Edge_{ij} = \left\{ (x, y) \middle| Surf_i(x, y) = Surf_j(x, y) \geq Surf_k(x, y), \forall k \neq i, j \right\} \tag{11}$$

The fuzzification of the above definition will give the fuzzy edges:

Definition 8. The "*fuzzy edge between the ith and the jth surfaces*" is the fuzzy set of points at which these surfaces have almost equal values and both have values greater than or almost equal to those of other surfaces:

$$Edge_{ij} = Eq_{ij} \bigcap_{k \neq i, j} \left(Gr_{ik} \cap Gr_{jk} \right) \tag{12}$$

Where Gr_{ik}, Gr_{jk} and Eq_{ij} are fuzzy sets of points and fuzzy intersections are any t-norm such as minimum, product, etc.

Eq_{ij}: Fuzzy set of almost equality of the *ith* and the *jth* surfaces.

Gr_{ik}: Fuzzy set of the *ith* surface greater than or almost equal to the *kth* surface.

The membership functions of these fuzzy sets can be given by the functions shown in Figure 7.

The resulting fuzzy graph of the environment shown in Figure 4 is now shown in Figure 8.

THE PROPOSED PATH PLANNING APPROACH

The Rational

The obstacle avoidance and path planning scheme should have the following properties:

Figure 5: Generalized obstacles' and the goal's surfaces

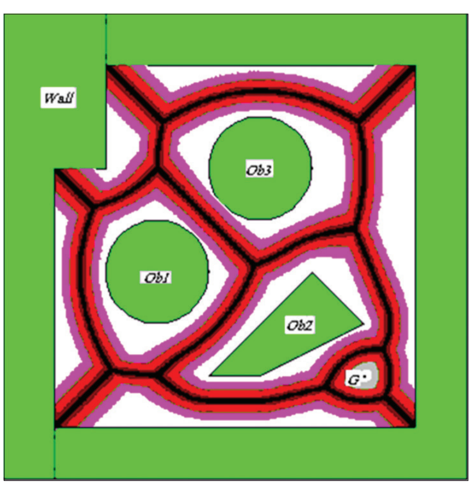

Figure 6: Fuzzification of the crisp graph

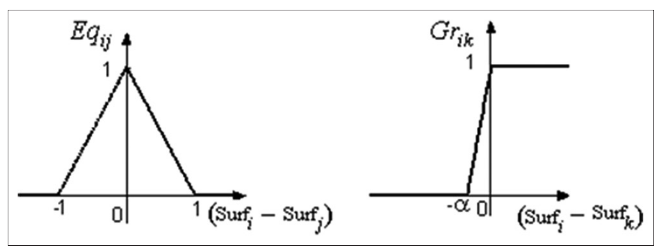

Figure 7: Functions used in finding fuzzy graph membership

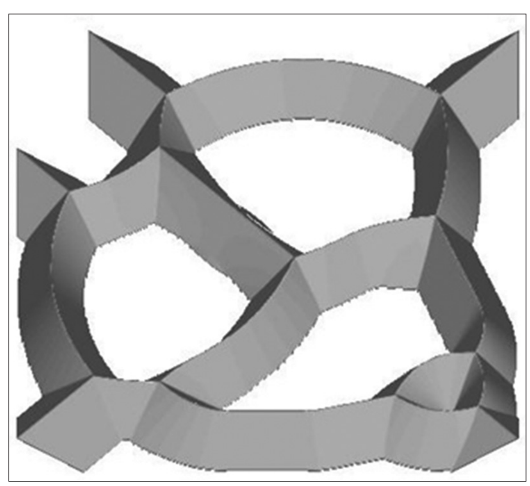

Figure 8: The fuzzy graph of the indoor environment

- The robot must move away from an obstacle in the normal direction when it is close to it.
- The above repulsive velocity must be proportional to the membership value at that fuzzy obstacle.
- The robot must move in the direction of fuzzy edges formed by the obstacles when it is located between them.
- The above drift velocity must be proportional to the membership value at that fuzzy edge.
- The robot must move toward the goal when it is close to it.
- The robot velocity must become zero at the goal.

Fuzzy Rules

Rule I *(Avoid the kth Obstacle):* If the robot position is in the region of the *kth* fuzzy obstacle with FMF $Ob_k(x, y)$, then the robot velocity is equal to V_{rep} in the opposite direction of the gradient of $Ob_k(x, y)$.

The output repulsive velocity of this rule is a crisp velocity:

$$\vec{V}_k = V_{rep}\,\hat{n}_k \quad , \hat{n}_k = -\frac{\vec{\nabla}Ob_k}{\left|\vec{\nabla}Ob_k\right|} \tag{13}$$

Rule II *(Attract to the goal):* If the robot position is in the region of fuzzy goal with FMF $Goal(x, y)$, then the robot velocity is equal to V_{att} in the direction of the goal.

The output attractive velocity of this rule is a crisp velocity:

$$\vec{V}_g = V_{att}\,\hat{n}_g \quad , \hat{n}_g = \frac{\vec{P}_g - \vec{P}}{\left|\vec{P}_g - \vec{P}\right|} \tag{14}$$

For each edge between the two obstacles, a rule can be defined for drifting the robot between the obstacles. Suppose it is desired to move the robot along the fuzzy edge between the *ith* and the *jth* obstacles in the direction that the *ith* obstacle lays on the left-hand side. A good moving direction is tangent to the curves $Ob_i - Ob_j = cte$. The unit vector of this movement $\hat{n}_{ij}$ can be given by

$$\hat{n}_{ij} = R_{-90^\circ}\frac{\vec{\nabla}(Ob_i - Ob_j)}{\left|\vec{\nabla}(Ob_i - Ob_j)\right|} \quad , R_{-90^\circ} = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \tag{15}$$

The above equation uses the gradient of the generalized obstacle surface (7). The rule of moving the robot in that direction can now be given as

Rule III *(Drift between the ith and the jth obstacles):* If the robot position is in the region of fuzzy edge between the *ith* and *jth* obstacles with FMF $Edge_{ij}(x, y)$, then its velocity is equal to V_{drift} in the direction of $\hat{n}_{ij}$.

When the robot is in the region between the goal and the neighboring *kth* obstacle, a rule for shifting the robot from the obstacle to the goal is used. The best direction is to move the robot in the direction of $\vec{\nabla}(Goal - Ob_k)$, namely

$$\hat{n}_{gk} = \frac{\vec{\nabla}(Goal - Ob_k)}{\left|\vec{\nabla}(Goal - Ob_k)\right|} \tag{16}$$

The above equation uses the gradient of the generalized obstacle surface (7) and generalized goal surface (10). The rule can be given as:

Rule IV *(Shift from the neighboring kth obstacle to the goal):* If the robot position is in the region of fuzzy edge between the goal and the neighboring *kth* obstacle with FMF $Edge_{gk}(x, y)$, then its velocity is equal to V_{att} in the direction of $\hat{n}_{gk}$.

Fuzzy Control Law

The fuzzy control law introduced in this paper uses one rule for avoiding each obstacle, one rule for shifting the robot in the direction of each fuzzy edge between obstacles, one rule for attraction to the goal and one rule for shifting the robot to the goal from each neighboring obstacle.

Suppose there are N fuzzy obstacles $Ob_k(x, y)$ in the environment and these obstacles form M fuzzy edges $Edge_{i_k j_k}(x, y)$. Also, suppose there is one fuzzy goal $Goal(x, y)$ and m edges $Edge_{gk}(x, y)$ are formed between the goal and the neighboring obstacles. A fuzzy system can now be implemented with Mamdani fuzzy inference engine, singleton fuzzier, and center of gravity defuzzifier. Then, by using the rules defined in Section 4.2, the reference velocity of the robot can be given as

$$\vec{V} = \frac{\sum_{k=1}^{N} Ob_k V_{rep}\,\hat{n}_k + \sum_{k=1}^{M} Edge_{i_k j_k} V_{drift}\,\hat{n}_{i_k j_k}}{\sum_{k=1}^{N} Ob_k + \sum_{k=1}^{M} Edge_{i_k j_k}} \cdots$$

$$\cdots \frac{+Goal\,V_{att}\,\hat{n}_g + \sum_{k=1}^{m} Edge_{gk} V_{att}\,\hat{n}_{gk}}{+Goal + \sum_{k=1}^{m} Edge_{gk}} \tag{17}$$

Sub-Optimal Path on Fuzzy Graph

After finding the FMF for fuzzy obstacles and fuzzy graph, suppose that the robot moves on the crisp graph formed by the fuzzy obstacles. Now, by selecting a suitable cost function the best path on this crisp graph can be found. Then by considering the best path, a directed crisp graph can be formed and the fuzzy graph can inherit these directions.

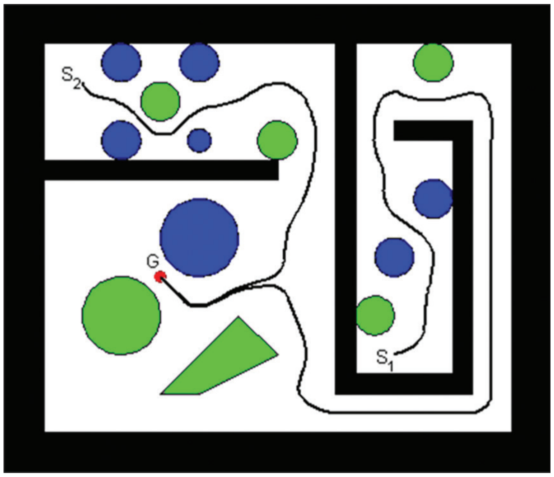

Figure 9: The environment used in simulations

The parameters used in fuzzy control law can be selected as

$$V_{drift} = 2V_{rep} = 2V_{att} \tag{18}$$

Hence, when the robot moves between the two obstacles, the repulsive velocities of the "obstacle avoiding rule" do not overcome the drift velocity.

Near the goal, all constants in (18) must converge to zero such that the robot stops at the goal without any overshoot.

Considering the Robot Dynamics

It can be seen from (17) and (18) that the reference velocity is proportional to V_{att}. Consequently, it can be concluded that the path followed by the robot does not ideally change by the variation of V_{att}, although the time of the trip would be different. Hence, the robot angular and linear velocities on the path can be controlled by adjusting V_{att}. This allows us to incorporate the robot dynamics into the path planning strategy.

SIMULATION RESULTS

All simulation results are obtained using MATLAB. Consider the environment shown in Figure 9. A key feature of this environment is that it contains many concave obstacles. Hence, if the starting point of the robot is behind of those obstacles, the robot must travel a path that that is not always directed towards the goal. Many LPP approaches (including the common fuzzy approaches) fall into local minima in this situation. In this simulation, two starting points S_1, S_2 are selected and it can be observed that the robot reached to the goal point G. In the first path (starting from S_1), the robot does not fall into local minima unlike many LPP approaches and in the second path (starting from S_2) the robot finds the correct path among many obstacles.

CONCLUSIONS

This paper proposed a new global fuzzy path planning approach. The new scheme is based on human behavior dealing with obstacles and goals. The resulting paths are sub optimal and the robot does not fall into local minima unlike other fuzzy approaches. The simulation results showed that the robot position has a global convergence to the goal. Future research is being done for finding the sufficient conditions for global convergence and improving the robot performance.

REFERENCES

1. T. Nakashima, T. Yakoh, T. Murakami, K. Ohnishi," Control of a wheeled mobile robot with two image processing grades," in Proc. IEEE Int. workshop Adv. Motion Control, pp.586-589, 2000.
2. S. Thongchai, S. Suksakulchai, D.M. Wilkes, N. Sarkar, "Sonar behavior-based fuzzy control for a mobile robot," IEEE Int. Conf. Systems, Man, and Cybernetics, pp.3532-3537, 2000.
3. C. Barret, M. Benreguieg, H. Maaref, "Fuzzy agents for reactive navigation of a mobile robot," First Int. Conf. Knowledge-Based Intelligent Electronic Systems, pp.649-658, May 1997.
4. D.K. Pratihar, K. Deb, A. Ghosh, "Fuzzy-genetic algorithms and mobile robot navigation among static obstacles," Proc. IEEE 1999 Congress on Evolutionary Computation, vol.1, pp.327-334, 1999.
5. F. Garcia, R. Mampey, "Mobile robot planning by reasoning both at itinerary and path levels," IEEE Int. Conf. Adv. Robotics, pp.1074-1080, Pisa, Italia, 1991.
6. Y.H. Liu, S. Arimoto, " Proposal of tangent graph and extended tangent graph for path planning of mobile robots," Proc. Robotics and Automation, pp.312-317, 1991.
7. M. Papa Georgiou, A. Steinkogler, "Real-time optimal control of moving vehicles in changing environments," IEEE Transactions on Control Systems Technology, vol.2, no.4, pp.447-454, Dec. 1994.
8. G. Ramirez, S. Zeghloul," A new local path planner for nonholonomic mobile robot navigation in cluttered environment," in Proc. IEEE Int. Conf. Robotic and Automation, pp.2058-2063, San Francisco, CA, Apr. 2000.
9. K.P. Valavanis, T. Hebert, R. Kolluru, N. Tsourveloudis, "Mobile robot navigation in 2-D dynamic environments using an electrostatic potential field," IEEE Transactions on Systems, Man, and Cybernetics, vol.30, no.2, pp.187-196, Mar. 2000.
10. J.T. Cho, B.H. Nam, "A study on the fuzzy control navigation and the obstacle avoidance of mobile robot using camera," IEEE Int. Conf. On Systems, Man, and Cybernetics, pp.2993-2997, 2000.

How to cite this article: Meigoli V, Barhaghtalab MH, Nikravesh SKY, Talebi HA. A New Global Fuzzy Path Planning and Obstacle Avoidance Scheme for Mobile Robots. Int J Sci Stud 2017;5(4):246-251.

Source of Support: Nil, **Conflict of Interest:** None declared.