

Navigation of Mobile Robot Using Type-2 Fuzzy System

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Abstract. One of the important problems of robotics is the navigation of mobile robots in uncertain environments that are densely cluttered with obstacles. The control of robots using the traditional control algorithms is not satisfactory as far as the navigational accuracy and the distance and time to reach the goal are concerned, when the robot is in a complicated surrounding. One of alternative and efficient ways of constructing a control system that explicitly deal with uncertainty is the use of fuzzy systems approach. The paper is devoted to navigation of mobile robot using type-2 fuzzy system. The design principle of navigation algorithm using type-2 fuzzy system is presented. The fuzzy knowledge base that describes the relation between the input- current angle and distance signals and output signals that determine the robot turn angle is developed. The control rules of navigation and inference engine operations have been described. The comparative simulation results of robot navigation system demonstrate the advantage of the fuzzy navigation algorithm.

Keywords: Robot navigation · Type-2 fuzzy systems · Fuzzy obstacle avoidance

1 Introduction

The robot navigation problem is very wide and complex. The environments where robot moves may vary from static areas with fixed obstacles, to fast-changing dynamic areas with many moving obstacles. The environment is uncertain if no prior information available about the obstacles. In such environment, the basic aim is to safely move and reach the prescribed destination point by finding the shortest path without collision of the obstacles existing on the road of the robot [1, 2]. The problem is the design of a fast and efficient algorithm that will lead mobile robots to the destination point. The navigation algorithm should determine continuous motion from one configuration to the other for the given the initial and final configurations of a mobile robot and find such a motion if one exists.

Recently various methodologies have been purposed for mobile robot navigation [3–10]. The most widely used are Artificial Potential Fields (APF) [4], Vector Field Histogram (VFH) [5], VFH+ [6], local navigation [7], fuzzy navigation [8–11] techniques. Others are Dynamic Window Approach [12], Rule-Based Methods [13], agoraphilic [14], Rapidly-exploring Random Trees (RRTs) [15], RRT smooth [16], A star [17].

Artificial potential field method of obstacle avoidance is based on the repulsive potential field around the obstacle and an attractive potential field around the goal to force away or to attract the robot. Various version of APF has been developed for various environments. VFH uses the concept of potential field and two-dimensional Cartesian grid as a world model. But VFH is timely expensive. The used conventional path planning algorithms are basically time-consuming and have difficulties in navigation of an uncertain environment. Finding the shortest path to reach a goal is one of important problem in robot navigation. Different algorithms have been used for finding shortest path in different environments. The comparisons of some path finding algorithms are given in [18–22].

Fuzzy logic is one of the efficient techniques for navigation of mobile robots in uncertain environments. Fuzzy logic can be used to model human perception process and deal with uncertainties in the control process. Usually, fuzzy logic based control is based on fuzzy if-then rules that describe the locations and relative positions of mobile robot and obstacles. The developed fuzzy rules are basically direction based rules and they describe the action of a mobile robot in different situations. A layered goal-oriented motion planning strategy using fuzzy logic is developed in [9] for navigation of a mobile robot in an unknown environment. Due to simplicity and capability for real-time implementation of the fuzzy navigation system, it is implemented on a real mobile robot, Koala. The design of fuzzy obstacle avoidance for robot navigation is presented in [10, 11]. An obstacle avoidance algorithm based on the fuzzy matching of obstacle environment is presented in [24]. Fuzzy rules and procedure to perform fuzzy navigation for behaviour based robot navigation is presented in [11, 25]. As a result of using fuzzy logic, the number of rules to be determined is reduced and the design of the robotic controller is simplified. The evolutionary algorithms are also used for tuning of the fuzzy system in the path motion controller. In [26] evolutionary programming is used for designing fuzzy logic path planner and motion controller.

As shown, a number of techniques are applied to the control and navigation of mobile robots. Fuzzy navigation algorithms are based on the usage of fuzzy knowledge bases. Mobile robots are usually navigating in changing and unstructured environments characterizing with a large amount of uncertainties. Sometimes the type-1 fuzzy systems cannot handle such kind of uncertainties. In such cases, type-2 fuzzy sets are used to handle uncertainties and increase the performance of navigation system. The uncertainties in type-2 fuzzy systems can arise from different sources. The types of uncertainties are given in [27]. Because the membership functions of type-2 fuzzy systems are themselves fuzzy, they provide a powerful framework to represent and handle such types of uncertainties. In this paper, a mobile robot navigation using a type-2 fuzzy rule-based algorithm for obstacle avoidance is proposed.

The type-2 fuzzy sets introduced by Zadeh. Mendel and Karnik have further developed the theory of type-2 fuzzy sets [27, 28]. The theoretical background of interval type-2 fuzzy system and its design principles are described in [27–29]. In literature, various applications of type-2 fuzzy logic systems can be seen; such as robot control [30], prediction of hot strip mill temperature [31], for identification and control nonlinear system [32–37], credit rating [35].

In the paper type-2 fuzzy system is presented for navigation of mobile robot. The distance and the angle variables are applied for designing navigation system. The paper

is organized as follows. Section 2 represents the design of fuzzy rule base for obstacle avoidance using type-2 fuzzy sets. Section 3 represents the type-2 fuzzy inference mechanism for if-then rule base describing the obstacle avoidance. Section 4 represents simulation results of robot navigation system using different techniques. Section 5 gives the conclusions of the paper.

2 Obstacle Avoidance Using Type-2 Fuzzy System

In robot navigation, the fuzzy system focuses on the goal reaching, while keeping avoidance of obstacles. An example of scenarios that demonstrates obstacle avoidance is shown in Fig. 1. Here, the mobile robot uses the distance measure in order to detect the presence of the obstacle. After detection of the obstacle, the local sensor detects the left and right boundaries of the obstacle in the local sensing region. The sensor region is determined by the user on the base of characteristics of the sensor used. It is impossible to know the shapes and sizes of all the obstacles outside the sensing region. During avoidance of an obstacle, the boundary of the obstacle is further enlarged to ensure the safety of the robot. This expanded boundary is called the “safe boundary”. This ensures the safety of the robot during avoidance of obstacles. Each obstacle will have two different boundaries, the “real boundary” and the “safe boundary”, as shown in Fig. 1. The robot detects the real boundary of obstacles. Then the safe boundaries of obstacles are determined by controller calculations performed within the navigation algorithm.

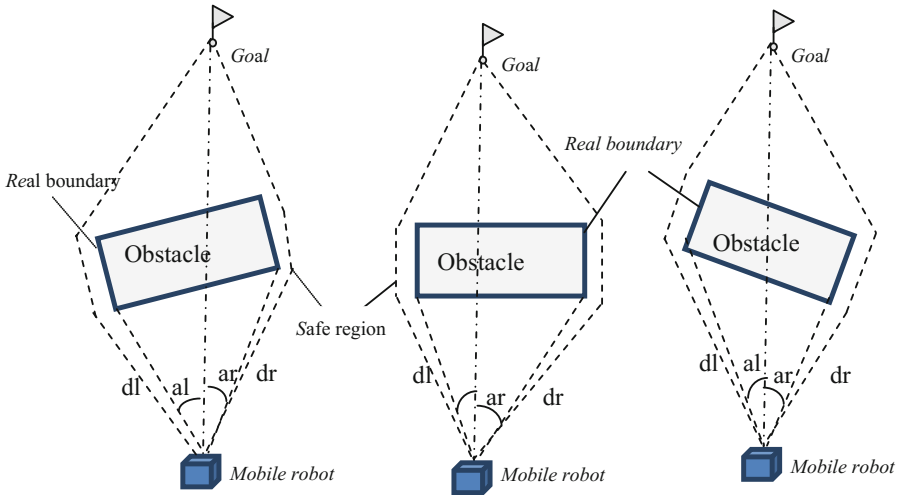


Fig. 1. Obstacle avoidance

The obstacle avoidance is carried out using knowledge base. This knowledge base includes If-Then rules that describe how the robot should avoid the obstacles.

The basic idea is to avoid the obstacle using shortest path and follow to the goal. In Fig. 1 three different scenarios are given in order to demonstrate turn angle of the mobile robot. Each scenario can be represented by one If-Then rule. Using different scenarios the rule base of the mobile robot is constructed. During designing of the rule base, the input variables are the left and right angle and distance variables, output variable is the turn angle of the robot. The left (al) and right angles (ar) are determined using the line connecting the robot and goal and the line connecting the robot and the real boundaries (left and right) of the robot. The left and right distances are determined as the distance between robot and left and right boundary points of the robot. Figure 2 describes the fuzzy If-Then rules for obstacle avoidance of mobile robot. In the rule base, the linguistic terms are used to represent the values of input and output parameters.

Rule 1: If $ar=S$ and $dr=M$ and $al=M$ and $dl=L$ then $ta=PS$
 Rule 2: If $ar=M$ and $dr=M$ and $al=S$ and $dl=S$ then $ta=NS$
 Rule 3: If $ar=M$ and $dr=S$ and $al=S$ and $dl=L$ then $ta=NS$
 ...
 Rule n: If $ar=VL$ and $dr=VL$ and $al=VL$ and $dl=L$ then $ta=NVL$

Fig. 2. Fragment of rule base

Here Z, VS, S, M, L, VL are linguistic terms and denote zero, very small, medium, large and very large, NVL, NL, NM, NS, Z, PS, PM, PL, PVL are negative very large, negative large, negative medium, negative small, zero, positive small, positive medium, positive large, positive very large.

Using the rule base and current values of input variables, the value of turn angle (ta) of the robot is determined. After determination of turn angle on the output of rule base, the safe angle is added to this turning angle in order to find the real turn angle of the robot for the avoidance of obstacle. Safe obstacle boundary is determined for the left and right side of the robot. The determination of the value of the input variables is performed as follows. At first, the distance between robot and obstacle are determined by sensors. At the same time by inspecting left and right borders of the obstacle from the target direction the left and right distances between the robot and left and right boundaries of the robot are determined. After detecting the left and right distances between robot and obstacle, the corresponding left α_l and right α_r angles are determined. Then the safe angle characterising the safe region is used for final detection of left and right angles. Based on the left and right angles (α_l and α_r) and also left and right distances (dl and dr) and If-Then rule base a corresponding decision on turn angle of the robot are made by the robot. The basic strategy is to select the direction that has the smallest distance from the robot to the goal. The calculated new turn angle is used to avoid an obstacle that will be:

$$ta(k) = F(\alpha_l, \alpha_r, dl, dr) \quad (1)$$

dl are dr left and right angles and left and right distances correspondingly.

In the rule base the values of input and output variables are represented using type-2 fuzzy sets. The type-2 fuzzy inference is applied for calculating output turn angle.

3 Type-2 Fuzzy System

The design of type-2 fuzzy model for the navigation of mobile robot is considered. As mentioned using angle and distance input variables and rule base the value of turn angle is determined. For these variables the term sets are determined. These values are determined using the highest and lowest value of the parameter and divided the value into three parts. Figure 2 describes the fuzzy values defined for the angle, distance and turn angle parameters. For simplicity, in the rule base, the input and output variables are scaled. The data can be easily transformed to the required range of the variables.

As mentioned, a type-2 fuzzy logic system can handle imprecise and uncertainty data to produce complex decision outcomes and minimize the effects of uncertainties. Type-2 fuzzy systems are applied for solution of different engineering problems [27–37]. In this paper, the type-2 fuzzy sets are applied for the navigation of robot.

The knowledge base given in Fig. 2 uses fuzzy IF-THEN rules including type-2 fuzzy values of the parameters in the antecedent and consequent parts of the rules. In the paper, the triangle type type-2 fuzzy sets are used to represent the fuzzy values of the parameters. In triangle type-2 fuzzy sets uncertainties can be associated to the mean. In the paper, the multi-input single output fuzzy rules are used. The type-2 TSK fuzzy rules used in this paper has the following form.

$$\text{IF } x_1 \text{ is } \tilde{A}_{1j} \text{ and } x_2 \text{ is } \tilde{A}_{2j} \text{ and } \dots \text{ and } x_m \text{ is } \tilde{A}_{mj} \text{ THEN } y_j \text{ is } \tilde{B}_j \quad (2)$$

where x_1, x_2, \dots, x_m are the input variables, y_j are the output variables, \tilde{A}_{ij} is type-2 interval fuzzy membership functions of the antecedent part assigned for the j-th rule of the i-th input, \tilde{B}_j is type-2 interval fuzzy membership functions of the consequent part for j-th rule. In the paper, triangle membership functions are used for \tilde{A}_{ij} and \tilde{B}_j .

The type-1 is extended to an interval type-2 fuzzy system by adding uncertainties in both antecedent and consequent parts of each rule. For each input i and rule j triangular membership functions (MF) with uncertain mean are used to represent fuzzy values of the parameters. Figure 3 depicts the membership functions with uncertain mean, used in the antecedent and consequent parts of the fuzzy rules.

As we know triangular membership function has the following formula.

$$\mu_A(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{c-l}, & l \leq x < c \\ \frac{r-x}{r-c}, & c < x \leq r \\ 0, & x > r \end{cases} \quad (3)$$

where l, r, c are left, right and centre parts of triangle. respectively.

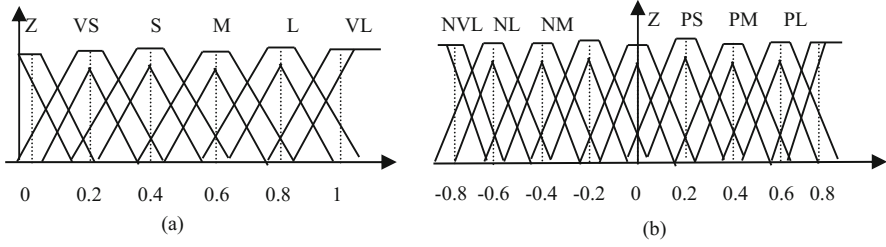


Fig. 3. Type-2 interval membership functions for - (a) input and (b) output variables

We apply this formula for designing type-2 membership functions and obtaining the upper and lower MFs. The lower $\underline{\mu}_{\tilde{F}}(x)$ and upper $\overline{\mu}_{\tilde{F}}(x)$ membership values are determined using (3).

In this paper, each membership function of the antecedent and consequent parts are represented by an upper and a lower membership functions. They are denoted as $\overline{\mu}(x)$ and $\underline{\mu}(x)$, or $\overline{A}(x)$ and $\underline{A}(x)$.

$$\mu_{\tilde{A}_k}(x_k) = [\underline{\mu}_{\tilde{A}_k}(x_k), \overline{\mu}_{\tilde{A}_k}(x_k)] = [\underline{\mu}^i, \overline{\mu}^i] \quad (4)$$

The inference engine can be implemented using “min” or “prod” t-norms operations. In this paper, “min” operation is chosen to calculate the firing strengths of the rules. As shown below the “min” operation is denoted as *. The firing strength of the j th rule is an interval type-2 fuzzy set determined by the left most and its rightmost points, which are calculated as follows:

$$\underline{f} = \underline{\mu}_{\tilde{A}_1}(x_1) * \underline{\mu}_{\tilde{A}_2}(x_2) * \dots * \underline{\mu}_{\tilde{A}_n}(x_n); \quad \overline{f} = \overline{\mu}_{\tilde{A}_1}(x_1) * \overline{\mu}_{\tilde{A}_2}(x_2) * \dots * \overline{\mu}_{\tilde{A}_n}(x_n) \quad (5)$$

where * is t-norm prod operator. After computing firing strength type reduction and defuzzification operations are performed. The type-reduction generates type-1 fuzzy set output. Defuzzifier uses this output and converts to a crisp number. Defuzzification provides mathematical formulas for the inner and outer bound sets which can be used to approximate the type-reduced set.

If we use the centre of sets type reduction then we need to compute the centroid of every consequent set, then computing a weighted average of these centroids.

$$Y = [y_l, y_r] = \int_{y^1} \dots \int_{y^M} \int_{f^1} \dots \int_{f^M} 1 / \frac{\sum_{i=1}^M f^i y^i}{\sum_{i=1}^M f^i} \quad (6)$$

Here Y is interval set that is determined by y_l and y_r , f^i is $[\underline{f}^i, \overline{f}^i]$, $y^i = [y_l^i, y_r^i]$ is centroid of the type-2 interval fuzzy set in consequent part.

Karnik and Mendel [27, 28] have shown that the two end points y_l and y_r depend on mixture of \underline{f}_i and \bar{f}_i values.

$$\begin{aligned} y_l &= y_l(\bar{f}^1, \dots, \bar{f}^M, \underline{f}^{L+1}, \dots, \underline{f}^M, y_l^1, \dots, y_l^M); \\ y_r &= y_r(\underline{f}^1, \dots, \underline{f}^R, \bar{f}^{R+1}, \dots, \bar{f}^M, y_r^1, \dots, y_r^M); \end{aligned} \quad (7)$$

Here \bar{f}_j and \underline{f}_j are determined using (4). Karnik and Mendel developed special iterative procedure [27, 28] for computing the values of y_l and y_r .

$$y_l = \frac{\sum_{i=1}^M f_i y_i^l}{\sum_{i=1}^M f_i}; \quad y_r = \frac{\sum_{i=1}^M f_i y_i^r}{\sum_{i=1}^M f_i} \quad (8)$$

Where $f^i \in F^i = [\underline{f}_i, \bar{f}_i]$, $y_i = [y_i^l, y_i^r]$. Karnik-Merndel have developed algorithm that find switch points L and R and compute two end points y_l and y_r of type-reduced set.

$$y_l = \frac{\sum_{i=1}^L \bar{f}_i y_i^l + \sum_{i=L+1}^M \underline{f}_i y_i^l}{\sum_{i=1}^L \bar{f}_i + \sum_{i=L+1}^M \underline{f}_i}; \quad y_r = \frac{\sum_{i=1}^R \underline{f}_i y_i^r + \sum_{i=R+1}^M \bar{f}_i y_i^r}{\sum_{i=1}^R \underline{f}_i + \sum_{i=R+1}^M \bar{f}_i} \quad (9)$$

Here switch points that can be calculated using Karnik-Merndel algorithm. The crisp outputs in defuzzification layer can be computed as follows:

$$y = \frac{y_l + y_r}{2} \quad (10)$$

Here y is defuzzified crisp output. Although the Karnik-Merndel algorithm is time consuming but it is efficient for the design of type-2 fuzzy logic system.

4 Simulation Results

Robot navigation software that includes the implementations of four algorithms is designed. The simulation of Potential Field Method (PFM), Local Navigation (LN), Vector Field Histogram Plus (VFH+) and also type-2 Fuzzy Navigation (T2FN) are performed. In simulation using the GUI interface, different obstacles having rectangular and circular form can be drawn. Start and goal positions of the robot can be specified. Then, a path planning algorithm is selected and a navigation of the mobile robot is performed. In all of the software runs below with algorithms, the gridSize has been taken as 1.0 and line length has been taken as 1. The number of points generated indicates the total number of points required to reach the goal with the selected line length. That is, the array that contains the path points has this number of members.

Figure 4 is a typical run of the Robot Navigation software with obstacles, using type-2 Fuzzy navigation. As can be seen from the figure, all obstacles were avoided successfully by the robot. The fuzzy algorithm avoided the obstacles by making decisions when the robot has approached the obstacles. Rule base with fuzzy inference mechanism is applied to find turning angle of the robot. As it is seen from the figure robot uses safe region during avoidance of obstacles.

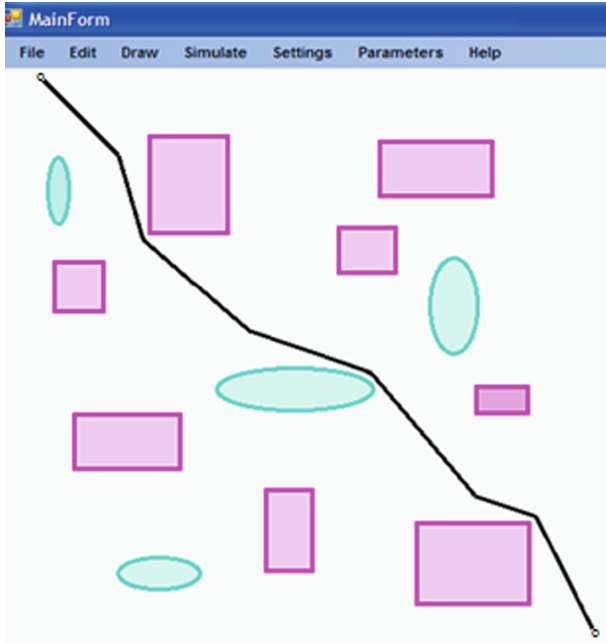


Fig. 4. Simulation result of type-2 fuzzy navigation algorithm

In next stage, we test fuzzy navigation algorithm using two different rule bases (RB): RB using angle and distance measures (left and right angles and distances) and RB using distance measures (left and right distances). In our simulation, RB that use angle and distance measures have given better results than other RB. Figure 5 demonstrate graphical simulation results. Table 1 demonstrates test results of FN algorithm with two different rule bases.

Another interesting simulation result is given in Fig. 6. Here, three obstacles are used with all four algorithms: Potential Field Method (PFM), Local Navigation (LN), Vector Field Histogram Plus (VFH+) and type-2 Fuzzy Navigation (T2FN). The obstacles are scattered around the path that the robot is expected to follow. Table 2 gives the statistics for Fig. 6 in terms of time to reach goal and distance measures. Here the number of generated point can be accepted as the length of the path) distance measure). The best result was obtained with the type-2 fuzzy navigation algorithm. The results in terms of time taken to reach the goal are different compared to the case shown in Fig. 6. It is interesting to note that there are differences in the time taken to reach the

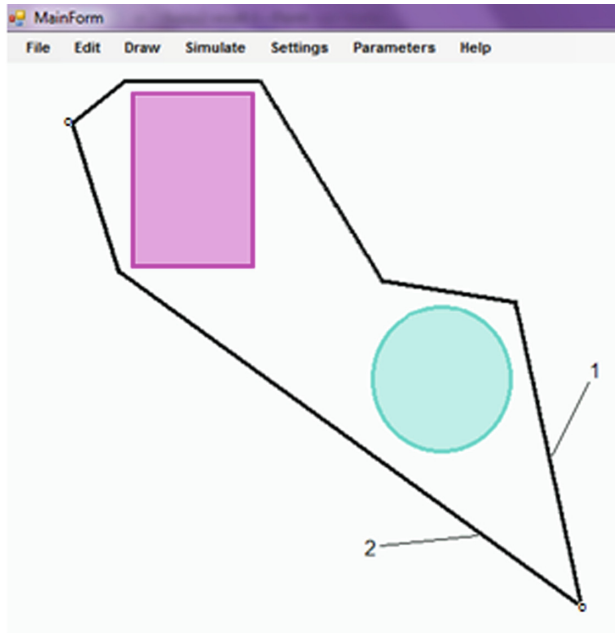


Fig. 5. Simulation result of type-2 fuzzy navigation algorithm using two different RBs: 1-RB using distance measures, 2-RB using angle and distance measures

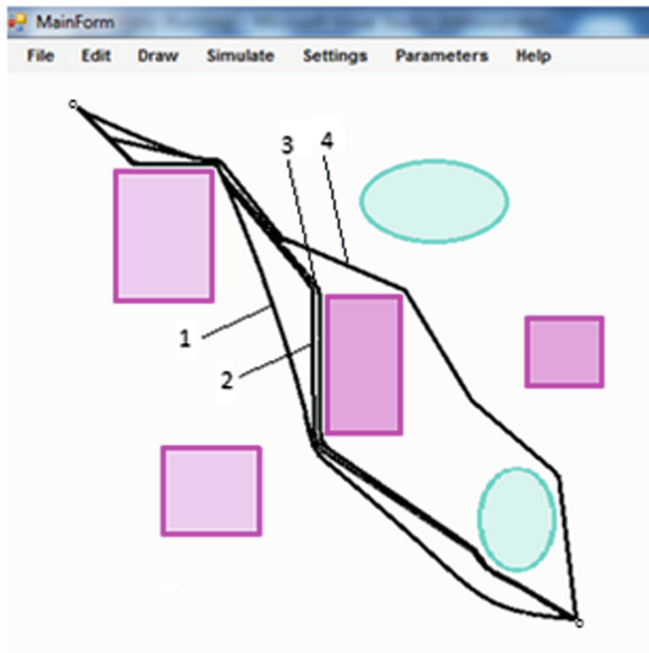


Fig. 6. Obstacle avoidance: 1 – APF, 2 – VFH, 3 – LN, 4 – T2FN.

Table 1. Statistics for Fig. 5

	Time taken to reach goal (ms)	Number of points
KB with distance measures	360	720
KB with angle and distance measures	380	674

Table 2. Statistics for Fig. 6

Algorithm	Time taken to reach goal (ms)	Number of points
PFM	21885	5304
VFH+	5599	5415
LN	398	5624
Fuzzy	370	5260

goal and the number of points generated by the fuzzy algorithm and other algorithms. The superiority of the T2FN algorithm is probably because of its resemblance to the intelligent human reasoning and decision-making process.

5 Conclusions

The type-2 fuzzy system is presented for mobile robot navigation in the presence of obstacles. The knowledge based is designed for obstacle avoidance. For simulation of type-2 fuzzy navigation and other above-mentioned navigation algorithms, a software package using C# have been developed. The workspace consisted of drawing different obstacles and robot starting and goal points on the screen. Various parameters of the algorithms can be adjusted manually in order to compare the advantages and disadvantages of the algorithms. Simulation of obstacle avoidance using type-2 fuzzy system has been performed. Comparison of simulation results of different algorithms has shown that the algorithm having shortest path among other navigation algorithms was the type-2 fuzzy navigation. The obtained results show that the algorithm having shortest path among other navigation algorithms was the type-2 fuzzy navigation.

References

1. Siegwart, R., Nourbakhsh, R.I.: Introduction to Autonomous Mobile Robots. MIT Press, Cambridge (2004)
2. Choset, H., et al.: Principles of Robot Motion, Theory. Algorithms and Implementations. MIT Press, Cambridge (2005)
3. Khatib, O.: Real-time obstacle avoidance for manipulators and mobile robots. In: Proceedings of IEEE International Conference on Robotics and Automation, St. Louis, MO, pp. 500–505 (1985)
4. Borenstein, J., Koren, Y.: Real-time obstacle avoidance for fast mobile robots. IEEE Trans. Syst. Man Cybern. **19**, 1179–1187 (1989)

5. Borenstein, J., Koren, Y.: The vector field histogram-fast obstacle avoidance for mobile robots. *IEEE J. Robot. Autom.* **7**(3), 278–288 (1991)
6. Wlrich, I., Borenstein, J.: VFH+: reliable obstacle avoidance for fast mobile robots. In: *Proceedings of the IEEE International Conference on Robotics and Automation* (1998)
7. Barber, R., Salichs, M.A.: A new human based architecture for intelligent autonomous robots. In: *The 4th IFAC Symposium on Intelligent Autonomous Vehicles*, Sapporo, Japan, pp. 85–90 (2001)
8. Wu, C.J.: A learning fuzzy algorithm for motion planning of mobile robots. *J. Intell. Rob. Syst.* **11**, 209–221 (1995)
9. Yang, X., Moallem, M., Rajni, V.P.: A layered goal-oriented fuzzy motion planning strategy for mobile robot navigation. *IEEE Cybern.* **35**(6), 1214–1224 (2005)
10. Abiyev, R., Ibrahim, D., Erin, B.: Navigation of mobile robots in the presence of obstacles. *Adv. Softw. Eng.* **41**(10–11), 1179–1186 (2010)
11. Abiyev, R.H., Günsel, I., Akkaya, N., Aytac, E., Çağman, A., Abizada, S.: Robot soccer control using behaviour trees and fuzzy logic. In: *12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016*. (Book Series: *Procedia Comput. Sci.* **102**, 477–484 (2016))
12. Fox, D., Burgard, W., Thrun, S.: The dynamic window approach to collision avoidance. *IEEE Robot. Autom.* **4**(1), 23–33 (1997)
13. Ehjimura, K.: *Motion Planning in Dgnarrtic Environments*. Springer, Heidelberg (1991)
14. Ibrahim, M.Y.: Mobile robot navigation in a cluttered environment using free space attraction “agoraphilic” algorithm. In: *Proceedings of the 9th International Conference on Computers and Industrial Engineering*, vol. 1, pp. 377–382 (2002)
15. LaValle, S.M., Kuffner, J.J.: Randomized kinodynamic planning. *Int. J. Robot. Res.* **2**(5), 378–400 (2001)
16. Abiyev, R.H., Akkaya, N., Aytac, E., Ibrahim, D.: Behaviour tree based control for efficient navigation of holonomic robots. *Int. J. Robot. Autom.* **29**(1), 44–57 (2014)
17. Yan, Z., Zhao, Y., Hou, S., Zhang, H., Zheng, Y.: Obstacle avoidance for unmanned undersea vehicle in unknown unstructured environment. *Math. Prob. Eng.* (2013)
18. Abiyev, R., Ibrahim, D., Erin, B.: EDURobot: an educational computer simulation programm for navigation of mobile robots in the presence of obstacles. *Int. J. Eng. Educ.* **26** (1), 18–29 (2010)
19. Erin, B., Abiyev, R., Ibrahim, D.: Teaching robot navigation in the presence of obstacles using a computer simulation program. *Procedia – Soc. Behav. Sci.* **2**(2), 565–571 (2010). Elsevier
20. Abiyev, R.H., Akkaya, N., Aytac, E., Günsel, I., Çağman, A.: Improved path-finding algorithm for robot soccers. *J. Autom. Control Eng.* **3**(5), 398–402 (2015)
21. Abiyev, R.H., Akkaya, N., Aytac, E.: Control of soccer robots using behaviour trees. In: *ASCC, Istanbul, June 2013*
22. Abiyev, R.H., Akkaya, N., Aytac, E.: Navigation of mobile robot in dynamic environments. In: *IEEE International Conference on Computer Science and Automation Engineering, CSAE 2012, Zhangjiajie, China*, pp. 480–484 (2012)
23. Abiyev, R.H., Bektas, S., Akkaya, N., Aytac, E.: Behaviour tree based control of holonomic robots. In: *Recent Advances in Mathematical Methods, Intelligent Systems and Materials, WSEAS Conference, Limasol, Cyprus*, pp. 54–59 (2013)
24. Guo, H., Cao, C., Yang, J., Zhang, O.: Research on obstacle-avoidance control algorithm of lower limbs rehabilitation robot based on fuzzy control. In: *6th International Conference on Fuzzy Systems and Knowledge Discovery*, p. 151 (2009)

25. Shirinzadeh, B., Parasuraman, S., Ganapathy, V.: Fuzzy decision mechanism combined with neuro-fuzzy controller for behavior based robot navigation. In: The 29th Annual Conference of the IEEE (2003)
26. Min, B.-C., Lee, M.-S., Kim, D.: Fuzzy logic path planner and motion controller by evolutionary programming for mobile robots. *Int. J. Fuzzy Syst.* **11**(3), 154–163 (2009)
27. Mendel, J.M.: *Uncertain Rule-Based Fuzzy Logic System: Introduction and New Directions*. Prentice Hall, Upper Saddle River (2001)
28. Karnik, N.N., Mendel, J.M., Liang, Q.: Type-2 fuzzy logic systems. *IEEE Trans. Fuzzy Syst.* **7**, 643–658 (1999)
29. Wu, H., Mendel, J.: Uncertainty bounds and their use in the design of interval type-2 fuzzy logic systems. *IEEE Trans. Fuzzy Syst.* **10**, 622–639 (2002)
30. Hagrass, H.: A hierarchical type-2 fuzzy logic control architecture for autonomous mobile robots. *IEEE Trans. Fuzzy Syst.* **12**(4), 524–539 (2004)
31. Castillo, O., Melin, P.: Intelligent systems with interval type-2 fuzzy logic. *Int. J. Innov. Comput. Inf. Control* **4**(2), 771–783 (2008)
32. Lin, Y.-C., Lee, C.-H.: System identification and adaptive filter using a novel fuzzy neuro system. *Int. J. Comput. Cogn.* **5**(1), 15–26 (2007)
33. Abiyev, R.H., Kaynak, O.: Type-2 fuzzy neural structure for identification and control of time-varying plants. *IEEE Trans. Ind. Electron.* **57**(12), 4147–4159 (2010)
34. Abiyev, R.H., Kaynak, O., Alshanableh, T., Mamedov, F.: A type-2 neuro-fuzzy system based on clustering and gradient techniques applied to system identification and channel equalization. *Appl. Soft Comput.* **11**(1), 1396–1406 (2011)
35. Abiyev, R.H.: Credit rating using type-2 fuzzy neural networks. *Math. Probl. Eng.* **2014** (2014). Hindawi Publications
36. Abiyev, R.H., Kaynak, O., Kayacan, E.: A type-2 fuzzy wavelet neural network for system identification and control. *J. Franklin Inst. Eng. Appl. Math.* **350**(7), 1658–1685 (2013)
37. Kayacan, E., Oniz, Y., Aras, A.C., Kaynak, O., Abiyev, R.: A servo system control with time-varying and nonlinear load conditions using type-2 TSK fuzzy neural system. *Appl. Soft Comput.* **11**(8), 5735–5744 (2011)

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