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Original Article

A novel mobile robot path planning method based on neuro-fuzzy controller

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ABSTRACT: In recent years, the navigation of mobile robots has been of great interest. One of the important challenges in the navigation of mobile robots is the obstacle avoidance problem so that the robots do not collide with each other and obstacles, during their movement. Hence, for good navigation, a reliable obstacle avoidance methodology is needed. On the other hand, some of the other most important challenges in robot control are in the field of motion planning. The main goal of motion planning is to compile (interpret) high-level languages into a series of primary low-level movements. In this paper, a novel online sensor-based motion planning algorithm that employs the Adaptive Neuro-Fuzzy Inference System (ANFIS) controller is proposed. Also, this algorithm is able to distance the robots from the obstacles (i.e. it provides a solution to the obstacle avoidance problem). In the proposed motion planning algorithm, three distances (i.e. the distance of the robot from the obstacles in three directions: right, left, and front) have been used to prioritize the goal search behavior and obstacle avoidance behavior and to determine the appropriate angle of rotation. Then, for determining the linear velocity, the nearest distance from obstacles and distance from the goal have been used. The proposed motion planning algorithm has been implemented in the gazebo simulator (by using Turtlebot) and its performance has been evaluated. Finally, to improve the performance of the proposed motion planning algorithm, We have used type-1, interval type-2, and interval type-3 fuzzy sets, then, we have evaluated and compared the efficiency of the proposed algorithm for each of these fuzzy sets under specific criteria.

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1. Introduction

Nowadays, mobile robots, due to their ability to replace humans in many applications are growing up very fast [19]. These robots are widely used in space, defense, education, and industry and require safe navigation in different environments [4]. Of course, a specific platform and design are required for each specific mission and task [20]. Autonomous mobile robots usually have to be in environments where there is no prior information. This requires the robot to have an intelligent decision-maker based on sensor information to be able to plan its motion in an uncertain environment [1]. Different types of path-planning methods have been studied in the literature [27].

Fuzzy systems and neural networks as examples of intelligent systems are increasingly used in various applications [10, 26]. ANFIS is a class of artificial neural networks (ANN) that is dependent upon the Takagi–Sugeno fuzzy

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inference system [8]. This method takes advantage of both fuzzy and neural networks. Therefore, it can be a good decision-maker for many applications.

In [2] genetic algorithm is used to solve path-planning problems in a static environment. The Ant Colony Optimization Algorithm (ACO) is integrated with fuzzy logic for path programming in dynamic environments in [22]. The minimum rule-based Adaptive Neuro-Fuzzy Inference System (ANFIS) controller has been presented for the safe navigation of single and multiple mobile robots in a cluttered environment by using the sensor-based steering angle control which is proposed in [16]. In [1], neural networks are used to do both goal-seeking and obstacle-avoidance behavior. Firstly, the data sets are generated by two different fuzzy logic algorithms then neural networks learn from these data sets. In [21] a neural network equipped with statistical dimension reduction techniques has been used for better navigation. [25] has been able to design an adaptive fuzzy neural network planning method by using extreme learning machine (Extreme-ANFIS) which reduces the computational complexity of the traditional adaptive fuzzy neural netrwork. The genetic fuzzy method that helps to find the optimal movement in terms of time while moving safely in the environment is presented in [17]. In [15] front obstacle distance, Right obstacle distance, left obstacle distance, movement angle, left wheel, and right wheel speed are used to generate proper steering angle by ANFIS. Motion planning of mobile robots in unknown environments is faced with many uncertainties. [3] Deals with the design of an Interval type-2 fuzzy logic controller for the navigation of mobile robots in unknown and dynamic environments to overcome these uncertainties. In [6], in an industrial robot, an intelligent structure based on a self-learning fuzzy type-2 system is used for motion control.

TLBO is one of the evolutionary algorithms used for optimization. Like other nature-inspired algorithms, TLBO is also a population-based method and uses a population of solutions to proceed to the global solution. The population is considered as a group of learners or a class of learners. The process of TLBO includes two steps: the first step consists of the 'Teacher Phase' and the second step consists of the 'Learner Phase [18]. This algorithm can be used for optimization in different fields. For example, [5] uses this method for neural network optimization.

In this study, we use a laser scanner to measure the distance from obstacles to compute the steering angle, the priority of dangers, and linear velocity by ANFIS. For a better covering of uncertainties, we will use type-2 and type-3 fuzzy sets and compare their results.

The rest of this article is organized as follows: In part 2, the ANFIS structure is described with fuzzy sets of types 1, 2, and 3, respectively. Section 3 describes the proposed method and methodology used. Section 4 shows the simulation and results. And the conclusion is described in section 5.

2. Prerequisites

In this section, an overview of fuzzy systems of different types will be discussed.

2.1. Anfis with fuzzy type-1 sets

ANFIS was first introduced in [7]. ANFIS is a universal nonlinear approximator [24]. The two types of Fuzzy Inference Systems (FIS) can be classified as Mamdani-type and Sugeno-type. The ANFIS works based on the Sugeno-type neuro-adaptive learning technique. This technique is more compact and computationally efficient. Its capability to tune the parameters of membership functions compared to the Mamdani-type fuzzy system makes it a good choice for many applications. Fig. 1 illustrates the structure of the ANFIS [9].

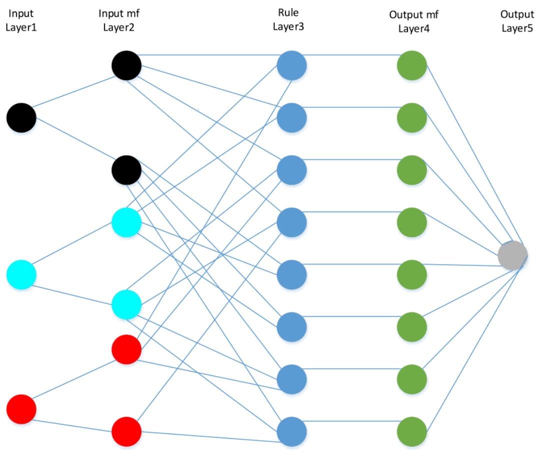

Figure 1: ANFIS structure with type-1 Fuzzy sets

2.2. Anfis with fuzzy type-2 sets

Zadeh introduced type-2 fuzzy as an extension of the type-1 fuzzy system to cover more uncertainties [12]. General type-2 fuzzy are computationally intensive. Computations become very simple when secondary membership functions are interval sets, in this case, Secondary memberships are either zero or one [23]. A general type-2 fuzzy and an interval type-2 fuzzy set is shown in Figures 2 and 3 respectively.

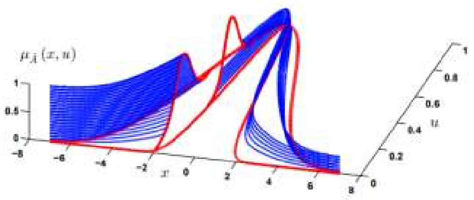

Figure 2: general type-2 fuzzy set [13]

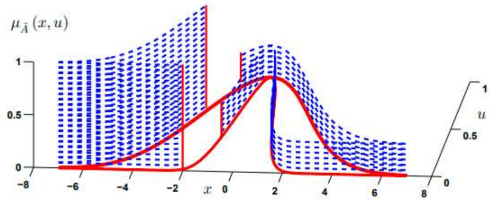

Figure 3: interval type-2 fuzzy set [13]

The relationship for the type-2 fuzzy set is shown in the blow. For an interval type-2 $\mu_{\hat{A}}(x,u)$ only can be 0 or 1.

$$\hat{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\hat{A}}(x,u)/(x,u) J_x \subseteq [0,1]. \tag{1}$$

In this work, the Interval type-2 Adaptive Network-based Fuzzy Inference System is used for decision-making more details can find in [23]. The used architecture is shown in Figure 4.

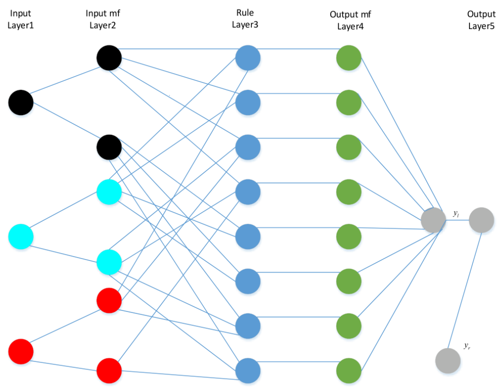

Figure 4: ANFIS structure with type-2 Fuzzy sets

The computations are so similar to the ANFIS with the type-1 fuzzy set. But in this case, we should compute the outputs for the upper and lower part of the membership functions and average them for the final output.

$$y = \frac{y_l + y_u}{2}. \tag{2}$$

2.3. Anfis with fuzzy type-3 sets

Interval type-3 fuzzy set can cover more uncertainty in contrast to type-1 and type-2 fuzzy sets. In this fuzzy set, the secondary membership function is an interval type-2 fuzzy set. This study tries to compare its ability in contrast to lower-type fuzzy systems. Unfortunately, using type-3 fuzzy systems is so limited. In [13], one structure is proposed for this. This study used the Takagi-Sugeno version of the proposed structure in [13]. The proposed structure, step by step, is given in appendix section. For more details, refer to [13].

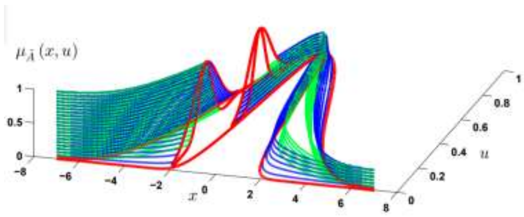

Figure 5: interval type-3 fuzzy set [13]

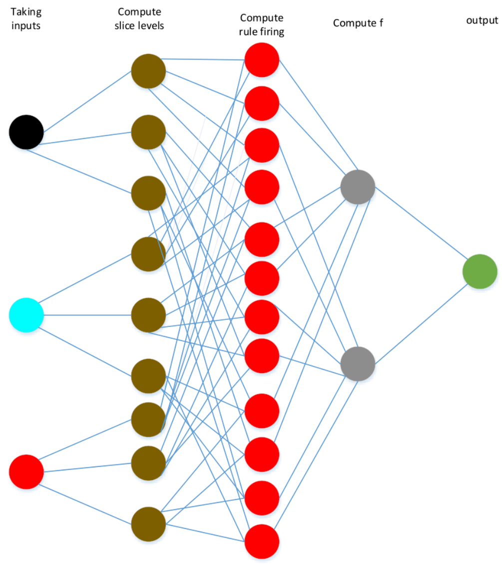

Figure 6: ANFIS structure with type-3 Fuzzy sets

3. Methodology

Differential drive robots are one of the simplest configuration of mobile robots [11]. In this study, the turtlebot mobile robot is used to verify the proposed algorithm in the gazebo simulator. The laser scanner is one of the best sensors to detect distance from obstacles. The distance of the robot from the front, right and left obstacles is used to determine the priority parameter and the angle of avoiding the obstacles, as well as the distance of the robot from the target and the nearest obstacle to determine the linear speed of the robot.

3.1. Priority parameter

This parameter prioritizes target-seeking behavior and obstacle-avoidance behavior. It actually determines how dangerous a situation is for the robot. for the more dangerous situation, this parameter will be closer to one.

The rules for generating the dataset are given in the appendix section.

3.2. Angle for obstacle-avoidance

When the robot encounters an obstacle, this angle determines the necessary direction to avoid this obstacle. Like the priority parameter, this parameter is also obtained according to the distance of the robot from the front, left, and right obstacles.

3.3. Final orientation of the robot

The final orientation of the robot at any moment should be such that it pursues both the goals of reaching the goal and avoiding obstacles. For this purpose, the final angle of the robot is adopted as follows:

$$\varphi = (1 - priority)(\arctan 2(y_{goal} - y_{robot}, x_{goal} - x_{robot})) + (priority)\theta. \quad (3)$$

3.4. Linear velocity of the robot

Safe, fast, and short path planning requires determining the linear speed of the robot in an appropriate way. If the robot is far from the target, it must have a higher linear speed to reach the target faster. But for the robot not to hit the obstacles, a compromise must be made between the distance from the target and the distance from the obstacles to determine the speed.

3.5. Pseudo-code for proposed algorithm

For the proposed sensor-based motion planning algorithm, the pseudo-code is presented as follows:

Algorithm 1 Proposed Algorithm

Require: Goal position
Ensure: A safe path from start to goal

while the robot does not reach the target **do**
    Check the distance of the robot from the obstacles and the target in time steps
    if there is no obstacle in the distance of less than one meter **then**
        1. Set priority parameter to zero
        2. Calculate the direction of the robot using equation (3) and apply it to the robot
        3. Calculate the linear velocity using the related ANFIS and apply it to the robot
    else
        1. Calculate the priority parameter using the related ANFIS
        2. Calculate the direction of the robot using equation (3) and apply it to the robot
        3. Move the robot with a constant linear speed of 0.9 m/s
    end if
end while

4. Simulation and results

In this section, simulation of the suggested ANFIS-generated planner in test environments is discussed. The tests were done using the Turtlebot robot in the gazebo simulator. But for better visualization, the paths using Python were shown. The ANFIS controllers with type-1, type-2, and type-3 fuzzy sets were trained with the Tlbo algorithm with population of 50. And robot path planning was implemented with each of them, and the results were compared with each other. Also, the proposed algorithm in [14] was implemented and the results were compared.

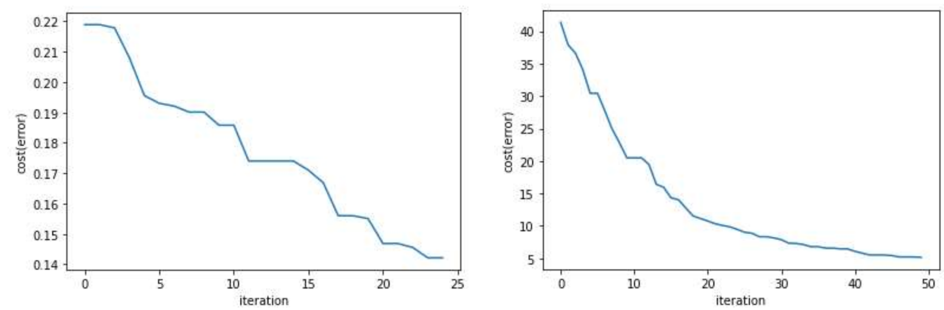

Figure 7: Convergence for fuzzy type-1 (angle and priority)

The tests were conducted in two environments, in the first environment, a small number of obstacles were placed with large distances to test the ability of the proposed method to find the target, but in the second environment, more obstacles were placed with small distances to test the ability of the proposed method to obstacle-avoidance.

The results show that when there is a little risk, the proposed system can reach the target in a smooth and fast movement, and when there are more risks, it can reach the target in a slower and discontinuous movement while avoiding existing risks. and this confirms the intelligence of the proposed algorithm.

Also, in order to measure the degree of safety of movement using the proposed algorithm, another test was conducted, and the number of movements without collision of the proposed algorithm was measured in two types of low-risk environments, such as the first scene, and high-risk environments, such as the second scene.

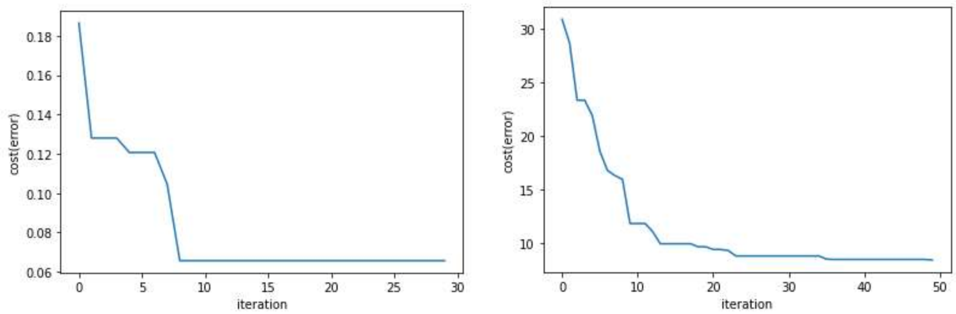

Figure 8: Convergence for fuzzy type-2 (angle and priority)

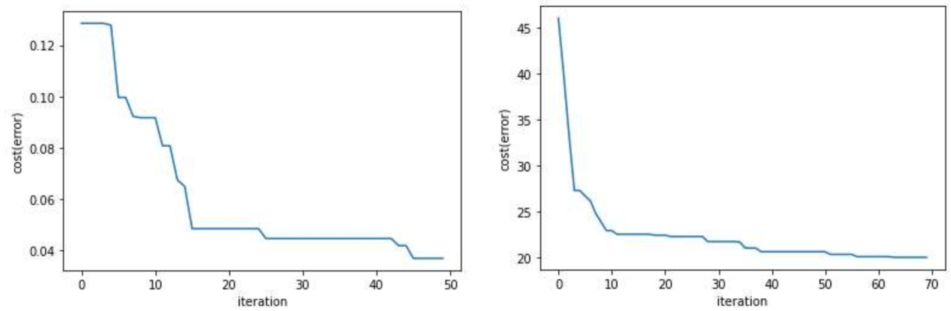

Figure 9: Convergence for fuzzy type-3 (angle and priority)

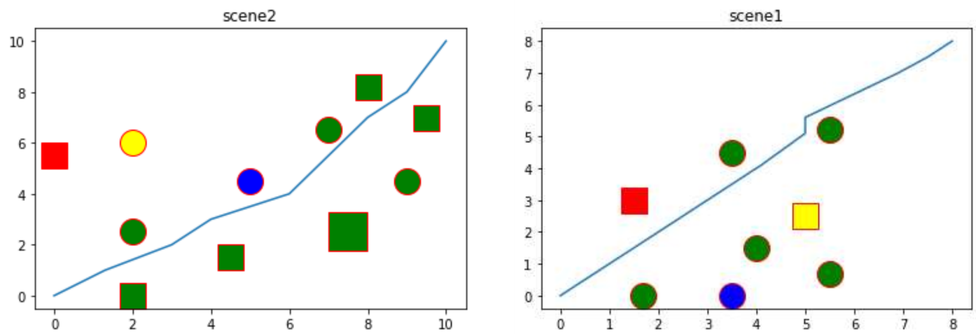

Figure 10: Results for fuzzy type-1

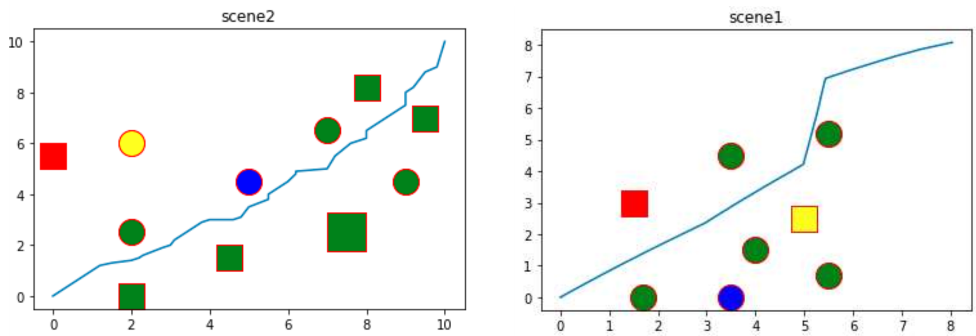

Figure 11: Results for fuzzy type-2

5. Conclusion

The new proposed structure was implemented using only a range finder sensor in unknown environments. This method uses obstacles' and goal's distance to determine the robot's linear velocity and final direction that they are sufficient to determine a good path from start to end. Indeed robot moves to the goal with a linear velocity that was calculated by related ANFIS and it stops and changes its direction when it faces an obstacle near than one meter. This strategy helps the robot to have a safe and short path to the end. The proposed structure was implemented using three different types of fuzzy sets. Three membership functions of low, medium, and high were considered for each ANFIS used. The proposed structure using all three types of fuzzy sets is safe, fast, and short

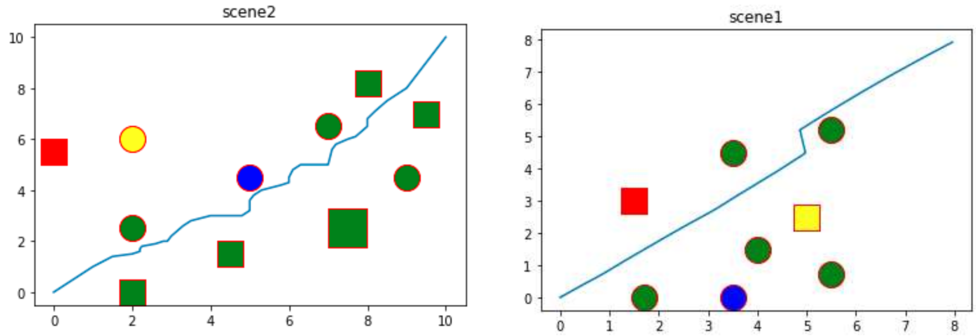

Figure 12: Results for fuzzy type-3

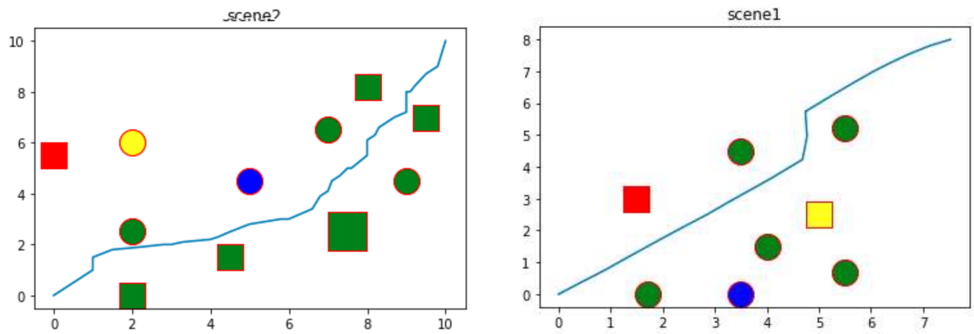

Figure 13: Results for proposed method in [14]

Table 1: Results for proposed algorithm in Scene1 and Scene 2

Algorithm		Scene 1	Scene 2
Type-1	Runtime	117	198
	Path length	11.58m	15.84m
Type-2	Runtime	108	189
	Path length	11.55m	15.52m
Type-3	Runtime	101	182
	Path length	12.14m	15.33m
The proposed method in [14]	Runtime	125	162
	Path length	11.49m	11.73m

Table 2: Results for proposed algorithm for safety measurment

Algorithm	Low-risk (6 environments)	high-risk (8 environments)
Type-1	5	5
Type-2	6	7
Type-3	6	6
The proposed method in [14]	6	5

in terms of distance. But in general, it can be said that fuzzy type- 3 performed better. The proposed method has less time than the proposed method in [14] in scene1 but has more time in scene2. It can be said that the reason is the use of adaptive linear speed. because the use of this adaptive linear speed when the robot is in a safe environment makes the robot move faster and when it is in an unsafe environment with moves at a lower speed, which helps both the high speed of the robot and its safety(in fact, the separate calculation of direction and linear speed of the robot helps to be safe and moves at a high speed when there is no danger and it can be useful in dynamic environments.). According to the results in Table 2, it can be said that the proposed algorithm has more safety than the proposed method in [14]. Roughly, it can be said that using fuzzy types 2 and 3 and comparing them with each other was a relatively new work that was used in this article. Also, the use of the Tlbo algorithm for training the parameters of the used Anfis could work well and can be used as a good method for training these systems in the field of mobile robots or any other field. For future works, the robot camera can be used and with the help of machine vision techniques, it can find the dimensions of the obstacles and use it as one of the inputs to determine the angle and the existing danger(priority parameter).

Also, to generate a set of rules for training the decision-making system, first, a human operator can perform the task of planning the robot, and then the obtained data can be used for training. Fuzzy type-3 combination with global algorithms such as A* can be considered. As a last word, with a slight change, the proposed method can be used in dynamic environments.

Appendix A – Anfis with type-3-fuzzy sets

1. Taking inputs $x_{1,\dots,}x_n$

2. Compute slice levels:

Consider the corresponding membership function for the inputs. $\hat{A}_i^j$ is the *j-th* MF for the *i-th* input. Then for different horizontal slice, levels compute the membership function that was introduced in the previous step. The horizontal slice level is $\mu_s = \widehat{\alpha}_k$

$$\widehat{\mu}_{\hat{A}_i^j|\mu_s=\widehat{\alpha}_k}(x_i^{'}) = m_{\hat{A}_i^j|\mu_n=\alpha_0}(x_i^{'}) + \sqrt{\ln(1/\widehat{\alpha}_k)\,\sigma_{V_i}^2}, \tag{4}$$

$$\underline{\mu}_{\hat{A}_i^j|\mu_s=\widehat{\alpha}_k}(x_i^{'}) = m_{\hat{A}_i^j|\mu_n=\alpha_0}(x_i^{'}) - \sqrt{\ln\left(\frac{1}{\widehat{\alpha}_k}\right)\sigma_{V_i}^2}, \tag{5}$$

$$\widehat{\mu}_{A_i^j|\mu_s=\underline{\alpha}_k}(x_i^{'}) = m_{\hat{A}_i^j|\mu_*=\alpha_0}(x_i^{'}) + \sqrt{\ln(1/\underline{\alpha}_k)\,\sigma_{V_i}^2}, \tag{6}$$

$$\underline{\mu}_{\hat{A}_i^j|\mu_s=\underline{\alpha}_k}(x_i^{'}) = m_{\hat{A}_i^j|\mu_n=\alpha_0}(x_i^{'}) - \sqrt{\ln\left(\frac{1}{\widehat{\alpha}_k}\right)\sigma_{V_i}^2}. \tag{7}$$

The $[\widehat{\alpha}_k,\ \underline{\alpha}_k]$ represent the uncertainty of secondary grades.

$$\widehat{\alpha}_k = \alpha_k^{1/\Delta}, \tag{8}$$

$$\underline{\alpha}_k = \alpha_k^{\Delta}. \tag{9}$$

$\widehat{\mu}_{\hat{A}_i^j|\mu_s=\widehat{\alpha}_k}/\widehat{\mu}_{A_i^j|\mu_s=\underline{\alpha}_k}(x_i^{'})$, are the upper memberships and $\underline{\mu}_{\hat{A}_i^j|\mu_s=\widehat{\alpha}_k}(x_i^{'})/\underline{\mu}_{\hat{A}_i^j|\mu_s=\underline{\alpha}_k}(x_i^{'})$ are the lower memberships of $\hat{A}_i^j$.

Where $\Delta \geq 1$ is a constant. The vertical slice at $x_i = x_i^{'}$ is an interval type-2 MF with standard division $\left[\frac{1}{\Delta}\cdot\sigma_{V_i}^2(x_i^{'}),\ \Delta\cdot\sigma_{V_i}^2(x_i^{'})\right]$.

$$\sigma_{V_i}^2(x_i^{'}) = \left(\underline{\mu}_{A_i^j|\mu_x=\alpha_0}(x_i^{'}) - m_{\hat{A}_i^j|\mu_s=\alpha_0}(x_i^{'})\right)^2/\ln\left(\frac{1}{\varepsilon}\right), \tag{10}$$

$$m_{\hat{A}_j^j|\mu_x=\alpha_0}(x_i^{'}) = \left(\underline{\mu}_{\hat{A}^j|u_u=\alpha_0}(x_i^{'}) + \widehat{\mu}_{\hat{A}_j^j|\mu_x=\alpha_0}(x_i^{'})\right)/2, \tag{11}$$

$$\widehat{\mu}_{\hat{A}_i^j|\mu_s=\alpha_0}(x_i^{'}) = \exp\left(-\frac{\left(x_i^{'} - C_{\hat{A}_i^j}\right)^2}{\widehat{\sigma}_{\hat{A}_i^j}^2}\right), \tag{12}$$

$$\underline{\mu}_{\hat{A}_i^j|\mu_s=\alpha_0}(x_i^{'}) = \exp\left(-\frac{\left(x_i^{'} - C_{\hat{A}_i^j}\right)^2}{\underline{\sigma}_{\hat{A}_i^j}^2}\right), \tag{13}$$

where $C_{\hat{A}_i^j}$, $\widehat{\sigma}_{\hat{A}_i^j}$, $\underline{\sigma}_{\hat{A}_i^j}$ are center, upper width and lower width of MF at horizontal slice level $\mu_s = \alpha_0$.

3. This step computes the rule firings.

$$\hat{z}^l_{\mu_s=\widehat{\alpha}_k} = \mathrm{T}_i^n \widehat{\mu}_{\hat{A}_i^l|\mu_s=\widehat{\alpha}_k}, \tag{14}$$

$$\underline{z}^l_{\mu_s} = \widehat{\alpha}_k = \mathrm{T}_i^n \underline{\mu}_{\hat{A}_i^l} \mid \mu_s = \widehat{\alpha}_k, \tag{15}$$

$$\overline{\mathrm{z}}^l_{\mu_s=\underline{\alpha}_k} = T_i^n \widehat{\mu}_{\hat{A}_i^l} \mid \mu_s = \underline{\alpha}_k, \tag{16}$$

$$\underline{z}^l_{\mu_s=\underline{\alpha}_k} = T_i^n \underline{\mu}_{\hat{A}_i^l} \mid \mu_s = \underline{\alpha}_k. \tag{17}$$

4. Compute f:

$$\hat{f}_k = \frac{\sum_{l=1}^M \left(\hat{z}^l_{\mu_k=\widehat{\alpha}_k}\hat{w}_l + \underline{z}^l_{\mu_k=\widehat{\alpha}_k}\underline{w}_l\right)}{\sum_{l=1}^M \left(\hat{z}^l_{\mu_k=\widehat{\alpha}_k} + \underline{z}^l_{\mu_k=\widehat{\alpha}_k}\right)}, \tag{18}$$

$$\underline{f}_k = \frac{\sum_{l=1}^M \left(\hat{z}_{\mu_n=\underline{\alpha}_k}\hat{w}_l + \underline{z}^l_{\mu_n} = \underline{\alpha}_k\underline{w}_l\right)}{\sum_{l=1}^M \left(\hat{z}_{\mu_n=\underline{\alpha}_k} + \underline{z}^l_{\mu_n} = \underline{\alpha}_k\right)}, \tag{19}$$

$$\hat{w}_l = \hat{C}_1x_1 + \hat{C}_2x_2 + \cdots + \hat{C}_nx_n, \tag{20}$$

$$\underline{w}_l = \underline{C}_1x_1 + \underline{C}_2x_2 + \cdots + \underline{C}_nx_n. \tag{21}$$

5. Compute output

$$y = \frac{\sum_{k=1}^K \left(\widehat{\alpha}_k\hat{f}_k + \underline{\alpha}_k\underline{f}_k\right)}{\sum_{k=1}^K \left(\widehat{\alpha}_k + \underline{\alpha}_k\right)}. \tag{22}$$

Appendix B – Tables

Table 3: Rules for generating the priority parameter dataset

FS (distance normalized to one meter)	RS (distance normalized to one meter)	LS (distance normalized to one meter)	Priority
0.2	0.2	1	0.89
0.2	1	0.2	0.86
1	1	0.1	0.74
0.25	0.5	0.75	0.76
0.4	0.6	1	0.7
0.15	1	1	0.71
0.25	1	0.5	0.75
0.15	0.15	0.15	0.92
0.5	0.15	0.15	0.9
0.2	0.1	0.1	0.93
1	0.15	0.15	0.87
0.25	0.1	0.1	0.92
1	1	0.15	0.74
1	1	1	0

Table 4: Rules for generating the θ parameter dataset

FS (distance normalized to one meter)	RS (distance normalized to one meter)	LS (distance normalized to one meter)	θ	Turn direction
0.2	0.2	1	87	Left
0.2	1	0.2	-76	Right
1	1	0.1	-79	Right
0.25	0.5	0.75	60	Left
0.4	0.6	1	67	Left
0.15	1	1	76	Left
0.25	1	0.5	-56	Right
0.15	0.15	0.15	86	Left
0.5	0.15	0.15	0	Front
0.2	0.1	0.1	76	Left
1	0.15	0.15	0	Front
0.25	0.1	0.1	83	Left
1	1	0.15	-74	Right
1	1	1	0	Front
0.2	1	0.2	-76	Right
1	1	0.1	-79	Right
0.25	0.5	0.75	60	Left
0.4	0.6	1	67	Left
0.15	1	1	76	Left
0.25	1	0.5	-56	Right
0.15	0.15	0.15	86	Left
0.5	0.15	0.15	0	Front
0.2	0.1	0.1	76	Left
1	0.15	0.15	0	Front
0.25	0.1	0.1	83	Left

Table 5: Rules for generating the linear velocity dataset

Goal Distance (distance normalized to start to end distance)	Nearest obstacle distance (distance normalized to three meter)	Linear velocity
1	1	0.7
1	0.8	0.6
1	0.6	0.47
1	0.4	0.12
1	0.2	0.03
0.8	1	0.68
0.8	0.8	0.56
0.8	0.6	0.43
0.8	0.4	0.09
0.8	0.2	0.03
0.6	1	0.62
0.6	0.8	0.52
0.6	0.6	0.39
0.6	0.4	0.07
0.6	0.2	0.03
0.4	1	0.57
0.4	0.8	0.48
0.4	0.6	0.35
0.4	0.4	0.05
0.4	0.2	0.03
0.2	1	0.5
0.2	0.8	0.42
0.2	0.6	0.31
0.2	0.4	0.05
0.2	0.2	0.03

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