Global and Local Robot Navigation Combination for Mobile Robot Obstacle Avoidance

Zead Mohammed Yosif[1*], Basil Shukr Mahmood [2], Saad Zaghlol Saeed[3]

[1] Mechatronics Eng. Department, University of Mosul,Mosul,Iraq
ORCID No: https://orcid.org/0000-0002-7291-486X
[2]Computer Eng. Department, University of Mosul,Mosul
[3] Mechatronics Eng. Department, University of Mosul,Mosul, Iraq
ORCID No.: https://orcid.org/0000-0002-8272-7080

Keywords

Mobile robot navigation, local path planning, global path planning, Adaptive Neuro-Fuzzy Inference System, dynamic obstacle avoidance.

Abstract

Nowadays, robots can be seen in different areas of life. Mobile robots can perform tasks that are too risky for a human. An essential issue in the mobile robot was addressed: driving the robot until it reaches its destination. A combination of global and local mobile robot navigation has been proposed to address the challenge of dynamic obstacle avoidance. A-star is utilized to discover an initial way between the and goal points. The ANFIS model is called when the obstacle is near the mobile robot to anticipate the collision. There are three inputs and two outputs in the adaptive neuro-fuzzy inference system. The inputs include the angle, distance, and relative speed between the mobile robot and any obstacles. The outputs are recommendations for a mobile robot's steering angle and speed. According to the simulation findings, the model can avoid static and moving obstacles in a static known environment. The proposed system achieves avoiding multiple obstacles. Compared with recent researchs, the proposed model shows the enhancement in path length, speed, and time required for mobile robot traveling.

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1. INTRODUCTION

Robot applications have spread widely and clearly in many applications (Anaz et al., 2023), where we can see robots in agricultural, industrial, and domestic applications. For this reason, the technologies used in robotics are developing remarkably and clearly, and these technologies depend significantly on the robot's applications. For example, the techniques used in robots that operate indoors are different from the technologies used in

*Resp author; zmyousif@umosul.edu.iq

robots that operate outdoors. There are many common technologies, even if the applications are different. One type of robot is the mobile robot. Autonomous mobile robots can be defined as robots that can move from one point to another without human guidance when there is information about the surrounding environment or part of it available(Chatterjee et al., 2013). There are two categories for mobile robot navigation. The global and local navigation (Yosif et al., 2021). A-star (A*) is One of the well-known algorithms that is used to find the path between two points in a static environment and the absence of dynamic obstacles(Duchoň et al., 2014).The A* is used by(Guruji et al., 2016) for mobile robot path planning, where the robot moves toward the target. As soon as it reaches a critical distance from the obstacle the controller calls the algorithm to find the path from the current position to the goal. The author in (Shahad M.Majeed, 2021) used A* to find the shortest path from start to goal with the help of image processing. The resarchers in (Al-Arif et al., 2012) compare Dijkstra and A* algorithms and found that A* consumes less processing time. The work in (Hernández and Giraldo, 2018) compares A* and PRM, whereas A* finds a shorter path RPM. There are many techniques used for mobile robot local navigation, one of these methods is the Adaptive Neuro-Fuzzy Inference System (ANFIS). This method combined fuzzy logic, which has a fast response, and neural networks, which are characterized by accurate results. The authours (Singh et al., 2009) suggested ANFIS makes a decision when the obstacle becomes very near to the robot. The ANFIS has four distance inputs from the robot to the obstacle in various orientations. whereas ANFIS suggests a mobile robot steering angle to avoid the obstacle. the authors (Pandey et al., 2016) introduced mobile robot navigation using ANFIS but for a static environment only. The distance between the robot and the obstacle is the input for ANFIS, and the output is a recommended steering angle for the mobile robot. (Gharajeh & Jond, 2020) use the ANFIS to avoid obstacles in the path of the mobile robot, whereas there are three inputs represented by distance on the right, left, and front of the mobile robot. The output is the steering angle suggested by ANFIS to avoid obstacles. The same idea was introduced by (Samadi Gharajeh and Jond, 2022) The input of ANFIS is three distance sensors and the output is the steering angle of a mobile robot, In this paper, we took the advantage of the two types of navigation and this tet us to combine the two types of mobile robot navigation. The initial path is generated by using the A* algorithm. The benefit from the second type is avoiding dynamic obstacles which pose a danger to the robot within the path that we found through global navigation.

2. PROPOSED METHOD

The first step in mobile robot navigation is reading the environment around the mobile robot. Defining the locations of stationary obstacles in the environment is known as reading the environment. The environment reading contains the positions of the start and target points. The A* algorithm is used to find the initial path between two points to avoid static obstacles. The ANFIS is called if the dynamic obstacle becomes close to the mobile robot. The proposed method includes two main parts. The first one is the generation of a path (initial path) between the target and the first point. The second one is the dynamic obstacle avoidance stage. Figure 1 includes the main parts of the proposed system.

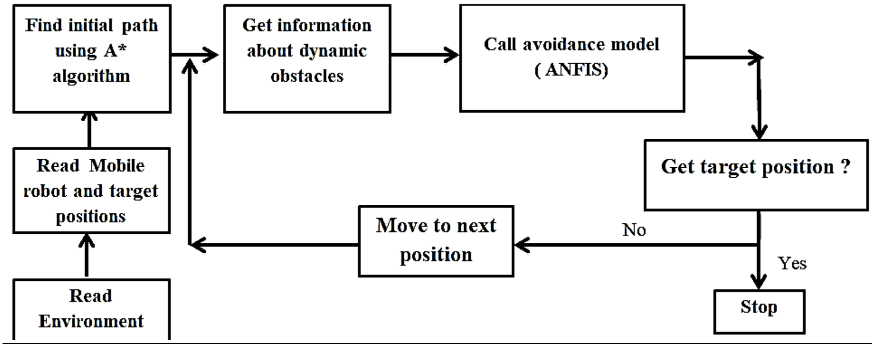


Figure 1. Proposed system

2.1 A* Algorithm

The problem of mobile robot path planning is still a research challenge, especially for an autonomous mobile robot. The question is answered through path planning " how should I get to where I am going ", there is no mention of time in path planning (Gasparetto et al., 2015).
A* is a heuristic algorithm that finds the shortest path between two points. A* is found from the Dijkstra algorithm(Yosif et al., 2022). Robotics and video games employ the A* algorithm to determine the route between two locations in a two-dimensional space. The heuristic property of A* can be achieved by the fitness function declared in the following :

$$\mathbf{f}(\mathbf{n}) = \mathbf{g}(\mathbf{n}) + \mathbf{h}(\mathbf{n}) \tag{1}$$

Whereas g(n) is the total cost from the start point to the current point, and h(n) is the cost from the current point to the target point. Figure 2 explains the basis of the A* algorithm. The A* algorithm provides a shorter path length and requires less time when compared to the RRT algorithm.

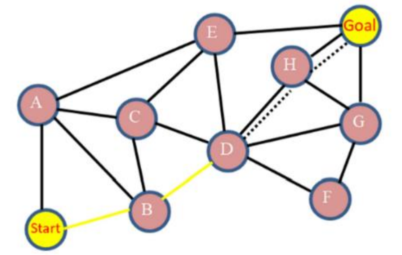


Figure 2. A* path planning example

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines Fuzzy logic and Neural networks. Whereas the rules of fuzzy logic are trained as a neural network. The ANFIS has multi inputs but one output (Gharajeh and Jond, 2020). Takagi-Sugeno fuzzy inference system combined with an artificial neural network to form ANFIS(Shafiullah et al., 2022). The Adaptive Neuro-Fuzzy Inference System consists of five layers in addition to input and output layers (Chen and Chang, 2018). The following figure 3 shows the main layers of the ANFIS system. The proposed model includes three inputs and two outputs. At the ANFIS input side, there are three inputs which are represented by angle, distance, and relative speed, all these criteria are between mobile robot and obstacle(s). The output of the model is two attributes which are represented by the suggested new mobile speed and steering angle. Figure 4 describes the ANFIS-suggested model.

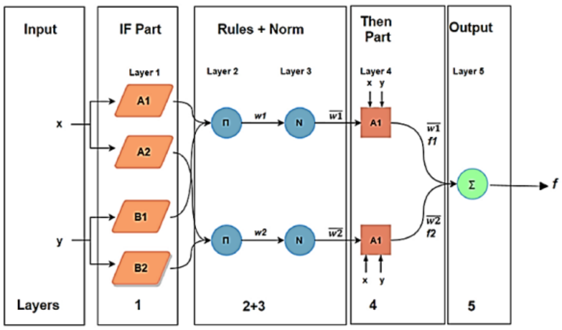


Figure 3. Structure of ANFIS model with two inputs(Armaghani and Asteris, 2021)

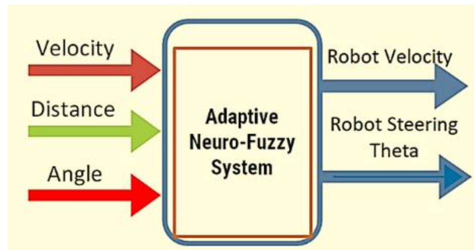
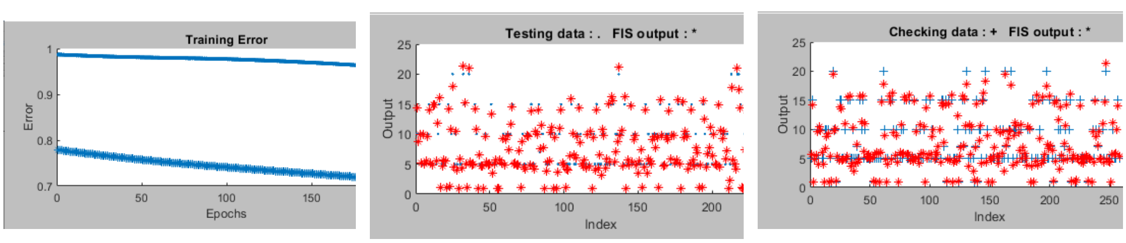


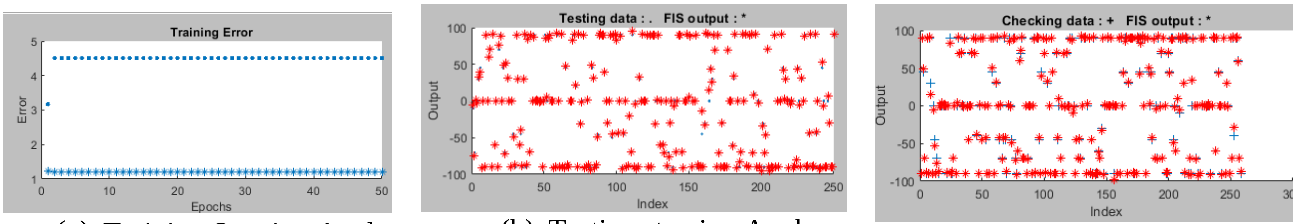
Figure 4. ANFIS proposed system

Five memberships have determined for each of the inputs and outputs, the rule can be generated by training a 5000 data record data set. The robot's velocity, distance from obstacles, and angle with those obstacles are the first three of each data row's five parts; the remaining two items are the two gANFIS outputs. The data ranges include an angle from -90 to 90, and distances from 1 to 120 cm, speeds from 1 to 50 cm/sec. the same ranges for output speed and angle. Three major sections make up the data set. The first part includes 4000 records. these records are used for training the ANFIS model. The remaining parts are subdivided into two parts, 500 samples for validating the model and another 500 records for testing. The test error for speed training is 0.7128, the validation error is 0.9582, and the speed training error is 1.0266. Here, Gaussian membership is employed. The test error is 3.93, the cross-validation error is 3.08, and the angle training error is 1.766. Figures 5 and 6 depict training, testing, and inspection. Figure 7 displays the ANFIS block diagram.



(a) Training speed (b) testing speed (c) checking speed

Figure 5. **A**daptive neuro-fuzzy systems model for mobile robot speed



(a) Training Steering Angle (b) Testing steering Angle (a) Checking steering Angle

Figure 6. Adaptive neuro-fuzzy systems model for mobile robot steering angle

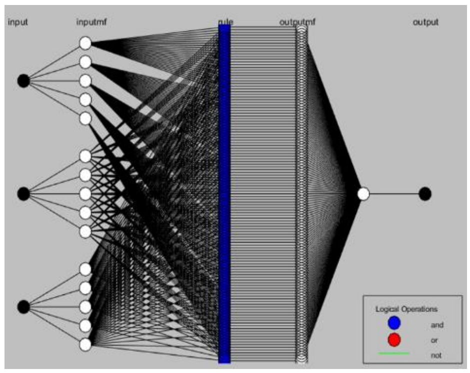


Figure 7. Adaptive neuro-fuzzy systems model block diagram

3. RESULTS AND DISCUSSIONS

The proposed environment dimension is 500 X 500 cm. each centimeter is represented by 1 pixel, therefor the area dimension in the simulation workspace is 500 X 500 pixels. Two types of environments have been proposed, the first type is the free environment which has dynamic obstacles only with no static obstacles. The second type of environment has both static and dynamic obstacles. Three dynamic challenges are presentd in Scenario 1. The mobile robot and its path are in the direction of the first and second dynamic obstacles. The initial obstruction has a -150-degree angle. The angles of obstacles 2 and 3 are -37° and -90°, respectively. The mobile robot begins avoiding it at point A in Figure 8 and returns to the path at point B. The mobile robot is traveling away from obstacle 2 once it reaches the beginning path at point B. Another obstacle (obstacle 3) is advancing toward the mobile robot as it goes from point B. The third obstacle is facing the mobile robot and is moving in a -90-degree angle. The most significant issue in this situation is the constant monitoring of the environment from point B to point C. In this instance, the mobile robot starts using the avoidance approach. The system calls the avoiding model once more, despite the mobile robot being in the avoidance strategy at a particular location C. The mobile robot resumes its starting journey at point D toward the objective after completing the third obstacle avoidance. After navigating obstacles, the robot covered 356 lengths. From start to finish, the robot needs 35 seconds. Figure 8 displays the details and traits we discovered for this situation. In terms of the locations of the mobile robot and the dynamic impediments, the second situation, which will be detailed shortly, is comparable to the first. In this scenario, the robot moves at a speed of 60 cm/sec while the dynamic obstacles move at speeds of 25 cm/sec, 25 cm/sec, and 15 cm/sec, respectively. The robot moves away from the third dynamic obstacle while it is coming directly into it in order to avoid a collision. Because the mobile robot and obstacle move more quickly than in the prior example, the steering angle is steeper than it was. The specifics of this case are shown in Figure 9. Three dynamic obstacles are part of a different scenario that is used in this situation (scenario 3). With a 35 cm/sec velocity, the initial obstacle travels toward the mobile robot from the upper right corner. The second dynamic obstacle is moving toward the mobile robot and its path at an angle of -45 degrees and a speed of 40 cm/sec. In contrast to obstacle 2, obstacle 3 is moving in the opposite direction at the same speed. The three moving objects provide a visible threat and collision risk as they reach the mobile robot. The recommended path has a length of 546 cm, and there is a 530 cm displacement between the starting point and the objective. After overcoming obstacles, the robot covered a distance of 660 meters. The robot needs 16 seconds to get from the start of the journey to the destination. As shown in Figure 10. Table 1 lists the features of the situations. The ANFIS responds to the system in 1.3 milliseconds.

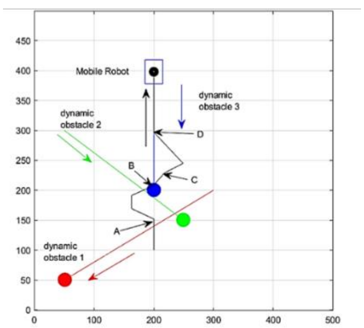


Figure 8. Three dangerous dynamic obstacles- (scenario 1)

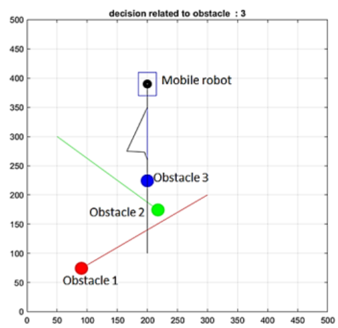


Figure 9. One dangerous obstacle and two safe obstacles, (scenario 2)

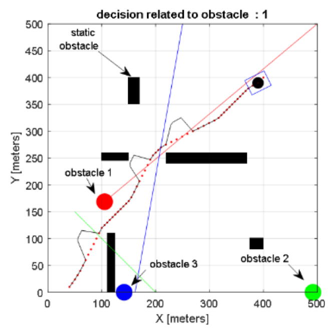


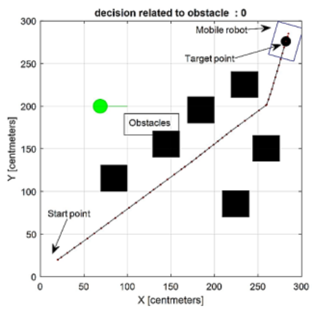
Figure 10. Environment with static and three dangerous dynamic obstacles (scenario 3)

Table 1. Characteristic of applied scenarios

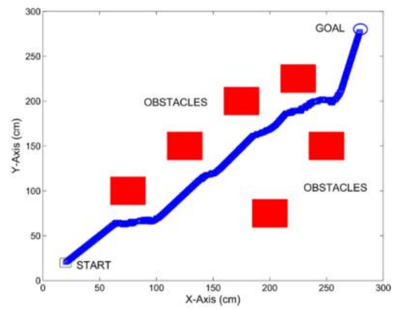
Characteristic	Scenario 1	Scenario 2	Scenario 3
Initial path length using A* (cm)	300	300	546
Duration of the generate initial route (sec)	0.6	0.6	8
Direct distance from the start to the end points	300	300	530
Path length after avoidance(cm)	356	330	660
Velocity of obstacle 1 (cm/s)	9	27	35
Velocity of obstacle 2 (cm/s)	8	24	40
Velocity of obstacle 3 (cm/s)	5	14	40
Velocity of robot(cm /s)	10	60	60
Relative velocity 1 - (cm /s)	16	61	94
Relative velocity2 - (cm /s)	16	82	82
Relative velocity3 - (cm /s)	15	70	100
Time from start to goal	35	9 sec	8 sec
No of iterations	78	72	115

4. COMPARISON WITH OTHER WORK

This work is compared with another paper that includes a static environment only and the second environment contains include dynamic obstacles. The first paper used a combination of neural networks and particle swarm optimization (PSO). This work, introduced by Pandey et al., 2020, uses a feedforward neural network to suggest a steering angle for a mobile robot depending on the distance between the robot and the obstacle which is neural network input. The PSO is used to optimize the path. in comparison to our work, we get a better model in terms of path length and time response. as clear in Figure 11(a) and table



(a) Proposed method



(b) Neural network and PSO (Pandey et al., 2020)

Figure 11. Testing proposed method and Neural network –PSO (Pandey et al., 2020)

Table 2. Comparison between Neural network PSO and the proposed method

Characteristics	**Neural network – PSO** (Pandey et al., 2020)	**Proposed method**
Path length	410 cm	387 cm
Traveling Time	39 sec	10 sec
Tiem required to find the initial path	0	5 sec
Total elapsed time	39	15 sec
Path length reduction ration	6 %	
Total time reduction ration	62 %	

5. CONCLUSIONS

A combination of global and local mobile robot navigation has been proposed to address the challenge of dynamic obstacle avoidance. The A* is a global path-planning navigation algorithm that is used to find the initial path from the start point of a mobile robot to its target. The local path planning is represented by Adaptive Neuro-Fuzzy Inference System to avoid dynamic obstacles in the path of the mobile robot. The proposed method shows the ability to avoid dynamic and static obstacles. The main challenge is the ability to avoid more than one obstacle at the same time. The proposed method compared with the other two papers that used static and dynamic obstacles respectively, the proposed method achieved better results and performance in terms of path length, speed, and response time.

Conflicts of Interest

The authors declared that there is no conflict of interest.

Contributions of Authors

The first and second authors contributed to designing the proposed system and collecting the results. The third author corrected and revising the language, giving appropriate directions on how to write, and analyzing and discussing the results contributed to collect all the information in this paper.

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