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Effective Route Planning of a Mobile Robot for Static and Dynamic Obstacles with Fuzzy Logic

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***Abstract*— Navigation of a mobile robot in cluttered environment while ensuring obstacle avoidance and maximum safety is indeed a challenging task. Route planning is an important issue in the field of autonomous mobile robots which makes them capable to travel from one position to another in various environments including both static and dynamic obstacles without any human intervention. This research is carried out with the purpose of designing and programming a mobile robot using two separated fuzzy logic controllers and developing an efficient algorithm in order to avoid both static and dynamic obstacles. In this work, four essential behavior controllers are designed and implemented onto the robot to assist its navigation towards the goal, i.e. goal reaching behavior, speed control behavior, goal searching behavior and obstacle avoidance behavior. For obstacle avoidance behavior, Sugeno fuzzy logic was applied. The simulation of this research was done by using MATLAB software where a mobile robot and some test environments with different complexity were created. Several navigation experiments were conducted and the robot's behavior were carefully observed. Analysis of the robot's performance validated the effectiveness of the proposed controllers and the robot could successfully navigate towards the goal in all experimental environments.**

Keywords— Mobile robot; route planning; fuzzy logic controllers; dynamic obstacle avoidance; Sugeno

I. INTRODUCTION

The use of robots to help humans to execute certain jobs is becoming more common nowadays. They can perform many tasks on a frequent basis, without needing safety and comfort requirements as humans. The word Robot is used for a wide range of machinery tools that are mobile. The origin of the word comes from Czech word "Robota" which means doing a labor by force [1]. In order to complete the assigned works, the robots need to pass a path defined by the operators. The path can be created by computer programs and the robots are able to control their moving plan to the final point. Robots of this kind are often fitted with number of sensors. Modern robotics of present time are making extensive use of various sensors such as ultrasonic sensors for the measurement of the surrounding environment. Moreover, many process planning operations and theories had been presented to overcome the happening fault in the dynamic environment [2].

Nowadays, numerous applications of mobile robots are implemented in various industries, from manufacturing to handling objects in the warehouse [3]. In dynamic and uncertain environments, robots should be active in the vicinity of many other moving factors, while their coming actions and reactions are not easy to predict [4]. Artificial Intelligence (AI) is a kind of soft computing that has the capability of mimicking the pattern of a human mind to deal with incomplete knowledge [5]. AI techniques like fuzzy logic generate solutions with reasonable accuracy while having relatively low computational complexity. This means that mobile robot can compute its solution in real time and is easy to design (as well as debug) due to the heuristic nature of fuzzy logic [6].

In this investigation, fuzzy logic is used to design the obstacle avoidance controller of the robot. Fuzzy logic embeds heuristic control knowledge in the form of if-then rules inside a machine and has proven to be practical and effective when the problem does not have a precise linear model. Fuzzy logic controllers have revealed a good level of robustness in face of large variability and uncertainty in the parameters. In this project, it is proposed to use Sugeno type fuzzy logic to design the robot static obstacle avoidance as well as dynamic obstacle avoidance. On the other hand, the goal searching behavior and speed control are designed by a very simple mathematical function. The sensors on the selected mobile robot are used to facilitate the robot navigation task. The project is implemented using MATLAB Fuzzy Logic Toolbox. The paper is divided into five sections. Section II provides a review of existing and related works. The proposed approach is described clearly in Section III while simulation results and discussion are presented in Section IV. In Section V, the conclusion of this paper is included.

II. RELATED WORK

In today's control systems, fuzzy logic approach is considered as a significant method in various fields. Four fundamental steps are taken in the process of fuzzy logic inference. In the beginning of the process, the input and output variables are determined, the second step states the fuzzy set, in the third phase fuzzy rules are described and the final phase is defuzzification [3].

Kim et al. [7] had attempted to solve path planning and impact of keeping away from obstacles problems. They made use

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of fuzzy logic system and potential field approach. In this regard, the paths of the robots are selected by a global path planner which lessen the potential value for every robot to its objective making use of a potential field. Afterwards, the path and the received direction of the global planner are improved by a local path plan which stops hitting against obstacles (static and dynamic) with the assist of fuzzy logic. Thus, testing the approach reveals that planning of path and keeping away from barrier are beneficial and helpful in the mobile robot systems.

Li and Choi [8] investigated a method that create a suitable path with having obstacle avoidance and moving within the quickest time. In their project, path planning of the mobile robot have become possible by a fuzzy logic based control system. Moreover, they used an ultrasonic sensor for distance detection of an obstacle, by considering the distance to obstacles and the angle between the robot and the target. Both robot's wheels velocities were under control. The outcomes demonstrated the speed of wheels in right and left direction. By using fuzzy logic, the outcomes of the simulation showed efficiency in avoiding from obstacles in an unstructured environment. Liew [9] addressed the performance of using fuzzy logic controller in a mobile robot as it avoids the obstacles. Implementation of different approaches, sensors and controllers able the robot to interface with an unstructured surrounding. The robot is equipped with two inputs and outputs that controlled two motors. The ultrasonic sensorial systems are fitted in. Identifying the barriers through sensors make the controller active to keep away from hitting. The result of the performance revealed that the robot is responsive to various kinds of barriers as anticipated.

Over the last decade, many researchers proposed solutions to deal with the robot path planning problem. Potential field method and its variant, is one way which used mostly. The fundamental thought about this approach is filling the robot environment with a potential field in which the robot is attracted to the target position and is repulsive away from obstacles. In every position, the robot computes the position that has the global minimum repulsive force and moves toward this position, and repeats this method as much as it is needed until it reaches its target [10].

Motion planning is an important issue in the field of mobile robotics. Therefore, path planning of mobile robot has been giving a great deal of consideration. Realistically, motion control planning of an autonomous mobile robot cannot rely on apriority knowledge of the surrounding environment. The mobile robot should make use of its sensors to get the environment information and plan motion consequently [11]. It has been revealed that classical approaches experience many disadvantages as many computational functions are required due to the great complication of real world spaces. In order to succeed in dealing with restrictions, scholars have integrated different methods, e.g. neural networks, genetic algorithms, ant colony optimization, particle swarm optimization, simulated annealing, and fuzzy logic [12].

III. METHODOLOGY

A. Fuzzy Logic Controller Design

Two separated Fuzzy Logic Controllers (FLC) are designed for robot obstacle avoidance behavior, one is for static and the other one is for dynamic obstacles. Each controller is adequate to fulfill expectation in navigation of mobile robot.

B. Static and Dynamic Obstacle Design

In this work, various geometric shapes of obstacles have been designed such as rectangles, squares, triangles, circles, curve-shapes, etc. In order to create a static obstacles, a function has been defined so inserting an obstacle in the environment is as simple as inserting a function in the main program codes. Complex geometric shapes can be created through overlapping and combinations of obstacles. In order to create a dynamic obstacles, it is possible to use the same functions of static obstacle and insert those functions in a while loop inside the main program codes.

C. Mobile Robot Design

Figure 1 illustrates the top-view schematic of the simulated robot the locations of its sensors. Nine proximity sensors are used which are located in the front of the robot and totally cover an area of 180° at the front of the robot. Each sensor covers a range of 20° and senses with the resolution of 1°. The main reason of implementing such as this number of sensors is dividing the front half of robot into nine equal sectors in order to increase the accuracy of obstacle detection.

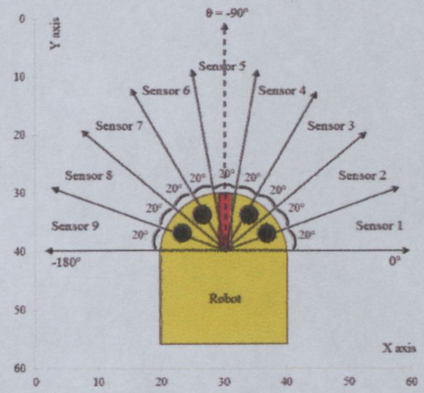

Fig. 1. Top view of the simulated robot

Figure 2 shows the obstacle detection area of the robot where it is designed to start detection from the down-right corner of the robot head at 0° and swiped CCW to the down-left corner at 180° while each sensor will cover 20° with the range of 80 units. It is designed for robot to have a radial cover range of 80 units for each 1° of sensing.

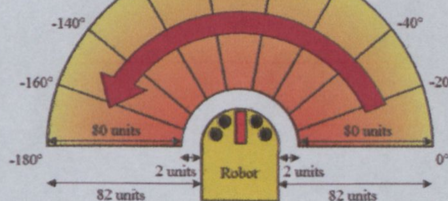

Fig. 2. Robot's obstacle detection area

It is designed for each sensor to have 30 samples in every 1° apart with the length of 80 units. The length of each sample will be around 2.67 units which is obtained as below:

$$\text{Sample Length} = \frac{\text{Radial Cover Range}}{\text{Total Sample Number}} \quad (1)$$

Each sensor returns a value between 0 and 30, based on the distance between the robot and obstacles. The sensors will return 0 when no obstacles are detected and may return '1 ~ 30' if obstacles are detected where the lower value returns the closer distance.

D. Mobile Robot Behaviors

Four primary behaviors for robot's navigation have been designed which are: Goal reaching behavior, Speed control behavior, Goal searching behavior and Obstacle avoidance behavior.

Goal reaching behavior is considered as a primary behavior with the highest priority. Once the goal visibility value becomes 1, the goal reaching behavior will be activated and the robot will immediately turn and move towards the goal. Speed control behavior is designed to control the robot's speed. Three different speeds are defined for the robot which are high speed, medium speed and low speed. Goal searching behavior makes the robot available to turn slowly and gradually towards the goal. To perform goal searching process, it is needed for robot to know the difference angle between the goal location and robot location (α) to find how much angle is needed for robot to turn towards the goal.

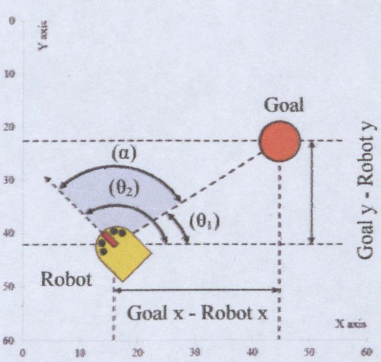

Fig. 3. Robot-Goal difference angle

As it is shown in Figure 3, suppose θ_2 is the robot heading angle and θ_1 is the angle between the robot and the goal which can be obtained as below:

$$\theta_1 = \arctan((\text{Goal y} - \text{Robot y}) / (\text{Goal x} - \text{Robot x})) \quad (2)$$

Hence, the Goal-Robot difference angle (α) can be calculated as below:

$$\alpha = (\theta_2 - \theta_1) \quad (3)$$

In order to make the robot available to increase its rotation angle towards the goal gradually, the incremental goal-robot difference angle can be defined as below:

$$\text{Incremental goal-robot difference angle} = \frac{-\alpha}{r} \quad (4)$$

where, α is the goal-robot difference angle and r is the robot turning control variable ($r = 1, 2, 3, \ldots$ n).

The larger value of r, the slower turning towards the goal. In this project, the value of r has been set to 72. The negative sign in equation (4) is applied for robot turning direction towards the goal.

The obstacle avoidance behavior is categorized into two different behaviors which are static obstacle avoidance behavior and dynamic obstacle avoidance behavior. Figure 4 illustrates the flowchart of the priority in executing the behavior of mobile robot.

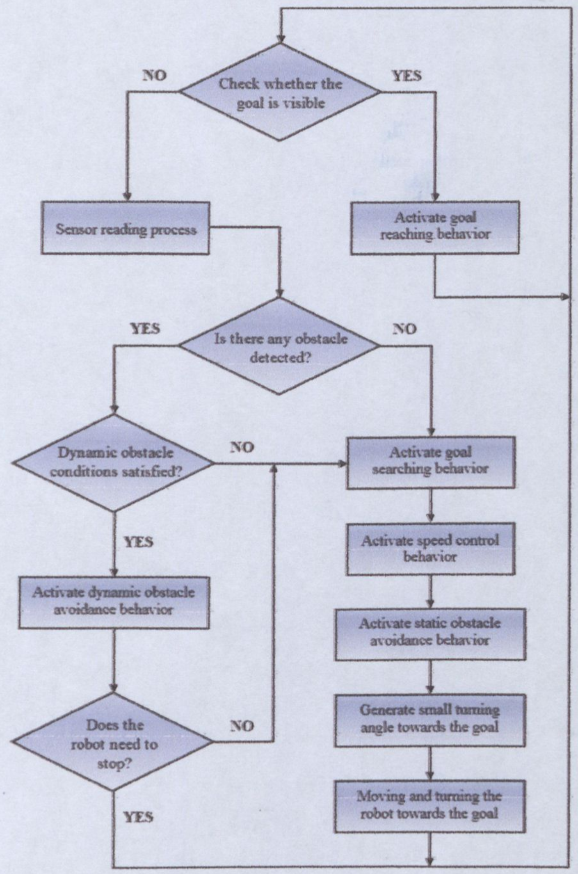

Fig. 4. Mobile robot behavior

E. Static Obstacle Avoidance Fuzzy Controller

A Sugeno Fuzzy Inference System (FIS) is designed for robot in order to make it available to avoid from colliding with static obstacles .As shown in Figure 5, it is designed that all 9 crisp numerical inputs of this fuzzy controller (which are the sensors outputs) are fuzzified with the same five membership functions which are named 'no obs', 'very close', 'close', 'far' and 'very far' where 'no obs' is stand for no obstacle which means there is no obstacle detected by the respected sensor.

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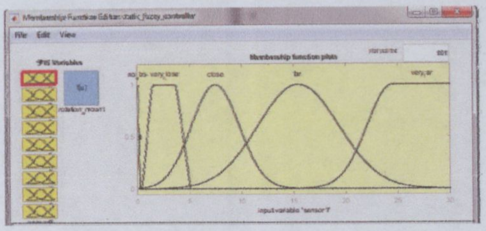


Fig. 5. Static FIS input membership functions

The range of the input membership functions is defined from 0 to 30 with respect to the sampling number of robot's sensors. The single output of the static obstacle avoidance fuzzy controller is defined as the amount and direction of the robot's rotation. The crisp numerical output values are fuzzified to 13 different linguistic variables such as 'no turn', 'very small turn right', 'large turn left', etc. After fuzzification step, it has been tried to create the optimum number of fuzzy rules out of the total number of them (which are 5^9 fuzzy rules) based on the experimental results. In this project, 87 fuzzy rules are created.

F. *Dynamic Obstacle Avoidance Fuzzy Controller*

Same as static fuzzy controller, a Sugeno Fuzzy Inference System is used to create dynamic obstacle avoidance fuzzy controller which makes robot available to steer away from colliding with dynamic obstacles. In order to distinguish between static and dynamic obstacles, an obstacle behavior detection algorithm is designed. This process will be started if any of the robot's sensors has an output of less or equal than 12. Thus, by satisfying this condition, the robot will stop immediately at its current position for 4 iterations while the outputs of the sensors are recorded separately in each iteration. The type of the detected obstacles is revealed by comparing the similarity of the sensors output in the first and fourth iteration, correspondingly. So, if all sensors outputs of these two iterations are exactly same as each other, the detected obstacle will be static otherwise it will be dynamic.

There are 4 types of dynamic obstacle movement in this project which are horizontal, vertical, oblique and rotational movement. In order to distinguish oblique/rotational movement from horizontal/vertical movement, the outputs of Sensor 2 to Sensor 8 through the previous first and fourth iterations are compared to each other, consequently. If at least one similar value can be found from this comparison, the obstacle movement will be considered as horizontal/vertical otherwise it will be oblique/rotational.

The dynamic obstacle avoidance fuzzy controller has 19 inputs which are the sensors outputs of the first and fourth iteration and also the oblique mode. As shown in Figure 6, it is designed that all 19 inputs of this fuzzy controller have the same two membership functions which are fuzzified to 2 different linguistic variables named 'zero' and 'one', respectively.

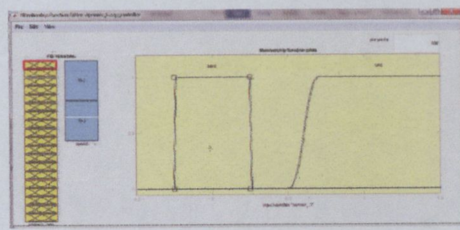
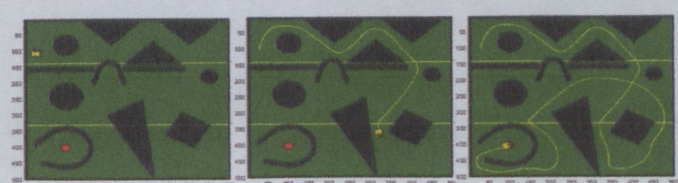


Fig. 6. Dynamic FIS input membership functions

The range of the input membership functions is defined from -0.5 to 1.5 with respect to the values of the inputs. This controller has two outputs. The first one is the subgoal angle which is designed to temporarily change the final position of the goal point and fuzzified to 10 linguistic variables such as 'very small turn right', 'medium turn left', 'very large turn right', 'no turn', etc. The second output is robot's speed where 3 linguistic variables are defined for this output which are 'stop', 'no change' and 'increase'. After finishing the fuzzification of the inputs and outputs of the dynamic fuzzy controller, they are applied to fuzzy rules for evaluation. In this project, 103 fuzzy rules out of the whole ones (which are 2^19 fuzzy rules) are selected to optimize the performance of the fuzzy system.

IV. SIMULATION RESULTS

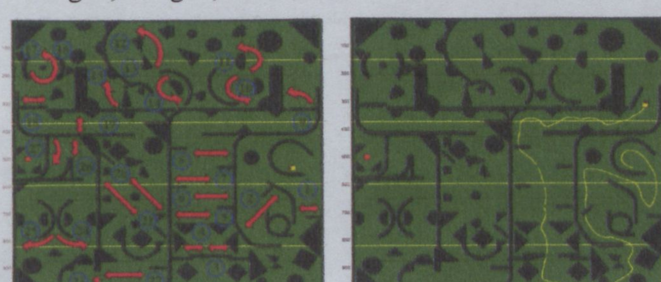
Different 2D experimental environments in this research are designed to perform the simulation process in which robot has to navigate from a given start location to a goal location while steers away from static and/or dynamic obstacles simultaneously. Figure 7 shows the robot's motion planning in the first environment where all obstacle were static.



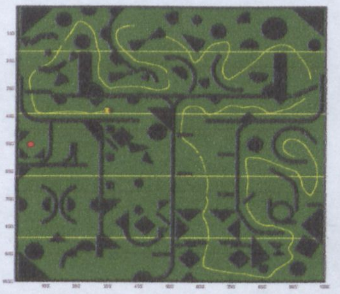
7(a) 7(b) 7(c)

Fig. 7. Motion planning in Environment 1

As shown in Figure 8, the next experimental environment was designed to have both dynamic and static obstacles where they were created based on many different shapes such as rectangles, triangles, circles, half-circles and sectors.



8(a) 8(b)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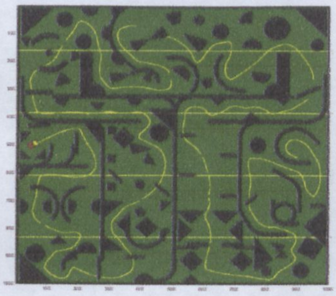
8(d)

Fig. 8. Motion planning in Environment 2

With having 27 different dynamic obstacles which have various motion directions, it is much more complex and cluttered experimental environment compared to the previous one. As illustrated in Subfigure 8(a), all dynamic obstacles are numbered consecutively and their different motion directions are indicated by red arrows.

From the conducted simulations, the robot had performed its navigation task well in all experimental environments. In order to perform an efficient robot's route planning for a particular type of the environment, it is required to tune the parameters of robot's behaviors such as goal searching behavior or speed control behavior to obtain optimum value. As observed through all experiments, the implemented obstacle detection algorithm is highly depended on both the obstacle's shape geometry and the robot's heading angle at the time of detection. It may sometimes cause the robot to come up with a risky decision to avoid colliding with obstacles (especially dynamic obstacles) during its navigation.

Decision making is also known as another significant factor in robot navigation. Based on the given situation, the robot is required to make decisions to activate the proper behavior. An appropriate balance of activation between static and dynamic obstacle avoidance behaviors can lead to an efficient performance. As a consequence, the robot can reach the goal in an efficient path planning when it is able to manage the priority of acting its navigation behaviors.

V. CONCLUSION

According to the simulation outcomes, all defined objectives of this project were achieved while two separated fuzzy logic controllers as an AI technique were designed together with other behavior controllers to perform an obstacle collision free navigation for mobile robot. Four primary behaviors were designed to help the robot's navigation which are goal reaching behavior, speed control behavior, goal searching behavior and obstacle avoidance behavior. In most cases, robot navigated well in various types of environment with no prior modification done to the robot. The simulations showed that the robot is capable of making good decisions such as deciding which junction and openings to enter.

Fuzzy logic controllers demonstrate to be an effective AI technique as it was implemented in this project while it makes robot capable to deal with uncertainty and produce good solutions for robot's navigation. They are fast to compute and easy to design.

As the further improvement it is recommended to design patterns of decision making for the robot where the consequences of a good decision by robot can lead to better efficiency and power saving. For instance, designing an initial top level controller using AI techniques to control the early behaviors of the robot such as speed control and goal searching or applying machine learning methods such as deep learning to design a controller which can learn by itself without human intervention.

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