Pathfinding with Obstacle Avoidance Using Fuzzy Logic

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***Abstract*—The abstract goes here (to be done later).**

I. Introduction

Self driving cars are being developed at almost every major car and tech company in the world right now. Although they are still relatively early in development, they are considered by many to be the future of personal transportation. To try and gain a better understanding of autonomous moving vehicles, in this project we attempt to recreate a simple one using a fuzzy logic system (FLS).

The goal of this project is to create and design a FLS that can guide a robot through different environments without colliding with any obstacles. Because of limited time and recourses we have not implemented this system for an actual vehicle or robot, instead, we worked with a simulation. Both the FLS and the simulation are created by ourselves. We then applied our FLS to our simulated robot in place of an obstacle avoidance algorithm.

II. Literature Review

There is already a lot of literature about trying to make a robot traverse an environment using fuzzy logic. In this section, we will briefly discuss three papers that are relevant to our problem.

In "Artificial Neural Fuzzy Logic Algorithm for Robot Path Finding" [1], X. Bajrami, A. Dërmaku and N. Demaku create and compare two fuzzy logic implementations to guide a robot from point A to point B in a simulated environment with obstacles.

The first implementation uses a combination of FLSs with mamdani-type inferrence and handmade rulebases and membership functions to guide the robot. The input (distances to closest objects and goal, angle towards goal and preferred turn) is used to determine acceleration levels for the left and right wheels of the robot for different objectives (like obstacle avoidance) and to determine different weights for those objectives.

The second implementation used an FLS with a Sugeno-type inference system, where the membership functions were trained using a neuro-adaptive learning method.

After running tests in a simulated environment, the two implementations were compared.

The first implementation in the paper comes close to what we have implemented. We have used the the distance to obstacles in three different directions as inputs to give information about the area the robot is moving towards. And give two angles of rotation, one to the left and one to the right, as outputs. These are combined to create a single rotation angle.

In "A Novel Hybrid Fuzzy A* Robot Navigation System for Target Pursuit and Obstacle Avoidance" [2], the researcher created a hybrid system to control a robot. The first layer of the system consisted of an A* algorithm. The A* algorithm is a path finding algorithm, it is considered to be very fast. The A* path finding layer calculated the optimal route to from the position of the robot to the end point, this route consisted of way points. The second layer of the system is a fuzzy logic system. This system had as input information about the next way point as well as about the nearest obstacle. With these pieces of information a speed and turning speed for the robot were chosen.

This paper used some techniques that can be very useful for our project. Since they used a moving end point in their simulations, their test scenarios where harder. However, the same principles they used to control their robot will apply to the robot in the simulations used in our project.

One problem that the researchers in [2] encountered, was that in some situation the fuzzy logic system would try to avoid an obstacle and by doing so, would not be able to move to the next way point. This is something to keep in mind for our project, but could be fixed by tweaking the membership functions.

In "Adaptive two layer fuzzy control of a mobile robot system" [3], a genetic algorithm has been used to adapt fuzzy rules in a two layer fuzzy logic system, which is then used by two robots to navigate towards a target without colliding. The genetic learning has been applied to generate a new layer of fuzzy rules that can be integrated into an already existing rulebase.

The first of the two fuzzy layers is used to determine the angle at which to continue moving, whilst the second layer determines the speed of the robot. By encoding the rulebase into a bitstring, Mohammadian *et al.* were able to modify the rulebases with a genetic algorithm using cross-over and single-point mutations over a number of generations. To do this they used a modified cross-over procedure that ensured that these bitstrings were cut only at points that defined boundaries between rules.

The paper concludes in noting that, altough most of their

tests resulted in a positive outcome, some had trouble at the corners of the tested driving areas. This suggests that genetic algorithms find a maximum in optimizing fuzzy systems that is not necessarily easily applicable to a change in, or extension of, the initial learning environment.

III. Proposed Approach

A. Design

Our Fuzzy Logic System uses three inputs and gives two outputs. The inputs we use are the distance to the nearest object in three different directions: front, front-left and front-right. The output is given in the form of two angles a left angle and a right angle, the robot will move in the direction of the combination of these two angles.
Our input variables have a mix of triangular and trapezoidal membership functions ( ). For all three inputs the range (in pixels) and membership functions are equal. The placement of the functions is chosen such that only a very small distance (about the size of the robot) is seen as a small distance, anything above about 5x the robots size is seen as a large distance and in between is a medium amount of distance. The functions have a reasonable amount of overlap since the random obstacle movement in our environment is cause for a decent amount of overlap.
We use a full rulebase of 27 rules for our system ( ). In general, the rules are chosen such that the robot makes sharper turns if the distance to the objects in front of it is smaller and will always prioritize a left turn over a right turn.

B. Implementation

We used python to build both the Fuzzy Logic System implementation and the simulated environment. For the simulations we primarily used the pygame package.

1) Fuzzy Logic System implementation: We implemented a variety of possible membership functions for our FLS implementation. Most of which use standard functions to return membership. For the triangular and trapezoidal membership functions, however, we used a sequence of if-else statements to calculate membership, rather than taking the minimum value from two lines. This way it was easier to make sure we do not accidentally devide by zero.
For our input and output variables, we simply record a name, range and list of membership functions. When calculating the membership, we return a dictionary with all memberships of a datapoint for the membership functions of the variable.
For our rules, we implemented AND and OR rules. AND rules can be calculated using the minimum operation or the algebraic product. OR rules can be calculated using the max operation or the algebraic sum.

2) Simulated Environment: The environment our robot moves around in is a box with an amount of obstacles. The obstacles are rectangular in shape and move in a random direction. Every certain amount of timesteps, the direction in which the obstacles move changes in a random new direction. The robot moves around in this environment at a fixed speed and has to avoid colliding with the obstacles. The change in angle of the robot at every tick is determined by the FLS.
The distance from the robot to an object are determined by raycasting. For each timestep, the robot casts two rays slightly around the desired direction. With this ray, the distance to the nearest object (that includes the walls of the simulation) is determined. The distance in that direction is then the smallest value returned from those two rays. This is done for angles around 0 degrees, 35 degrees and -35 degrees and the distances are passed to the FLS. The FLS then determines a left and right turning degree and the middle of those two angles is taken as the change in directions that the robot follows.

C. Link to repository

https://gitlab-fnwi.uva.nl/10989048/fuzzy_logic_final_project https://github.com/Yelvd/Fuzzy_logic_final_project

IV. Experiments and Results

A starting situation was created for the simulation. This starting situation consisted of the robot in the corner at the bottom left and 14 square obstacles of varying sizes placed around the field, see figure 1.

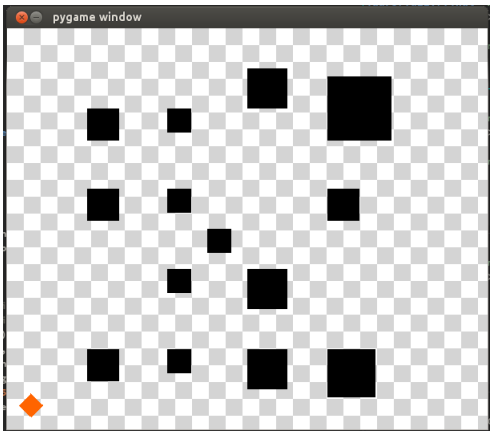

Fig. 1. starting situation for the simulation

The obstacle move each in there own random direction, after 30 frames they pick a new random direction. When colliding with an other object or the wall the obstacle rotate there direction vector 45 degrees clockwise each frame until they can move again. A simulation terminates when the robot collides with an obstacle or the wall. The data that was collected is the length of a simulation in frames. Frames where chosen as measurement unit instead of time since this allows us to speed up our simulations by unlocking the number of frames per second, the data is also more reliable because it is changed if the computer the experiment is run on cannot keep up with the simulation.

The following sets of speeds where chosen:

- Player: 2 pixels/frame, Obstacle: 1 pixels/frame

- Player: 2 pixels/frame, Obstacle: 2 pixels/frame
- Player: 2 pixels/frame, Obstacle: 4 pixels/frame
- Player: 6 pixels/frame, Obstacle: 6 pixels/frame

For each set of speeds two different types of terminate conditions where used. The first one being that the simulation terminates if the player makes a move that result in a collision with either an obstacle or the wall, on the other test the simulation terminated when the player collided with an obstacle or wall or when an obstacle made a move that resulted in a collision. For each set of speeds both termination conditions where run 20 times. The average frames until termination is reported below.

A. Results

V. Discussion

From the data there where two visible problems with the fls.

The first being that when the speeds increase the duration of the simulations decreases.This can be explained by the fact that the mfs use a distance in pixels to calculate the closeness of objects, the membership functions don't change based on the speed. The fls also does not have speed as one of it's inputs. This means that the fls has no way to correct for speed. When the robot moves at a higher speed the something that was 'far' for a lower speed might now be reached in one frame.

The follow problem that can be seen is that when the terminate conditions are such that the simulation is only terminated when the robot makes a move that results in a collision, the duration of the simulations is lower in all setups. A reason for this can be the fact that the fls does not look behind it self to check for possible collisions this means that it can be hit from behind or the side by an obstacle.

References

[1] X. Bajrami, A. Dërmaku, and N. Demaku, "Artificial neural fuzzy logic algorithm for robot path finding," *IFAC-PapersOnLine*, vol. 48, no. 24, pp. 123–127, 2015.

[2] A. P. Gerdelan and N. H. Reyes, "A novel hybrid fuzzy a* robot navigation system for target pursuit and obstacle avoidance," in *Proceedings of the First Korean-New Zealand Joint Workshop on Advance of Computational Intelligence Methods and Applications*, vol. 1, 2006, pp. 75–79.

[3] M. Mohammadian and R. J. Stonier, "Adaptive two layer fuzzy control of a mobile robot system," in *Evolutionary Computation, 1995., IEEE International Conference on*, vol. 1. IEEE, 1995, p. 204.