

Fusion of Probabilistic A* Algorithm and Fuzzy Inference System for Robotic Path Planning

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Citation: R. Kala, A. Shukla, R. Tiwari (2010) Fusion of probabilistic A* algorithm and fuzzy inference system for robotic path planning, *Artificial Intelligence Review* 33(4), 275-306.

Final Version Available At: <http://link.springer.com/article/10.1007%2Fs10462-010-9157-y?LI=true>

Abstract

Robotic Path planning is one of the most studied problems in the field of robotics. The problem has been solved using numerous statistical, soft computing and other approaches. In this paper we solve the problem of robotic path planning using a combination of A algorithm and Fuzzy Inference. The A* algorithm does the higher level planning by working on a lower detail map. The algorithm finds the shortest path at the same time generating the result in a finite time. The A* algorithm is used on a probability based map. The lower level planning is done by the Fuzzy Inference System (FIS). The FIS works on the detailed graph where the occurrence of obstacles is precisely known. The FIS generates smoother paths catering to the non-holonomic constraints. The results of A* algorithm serve as a guide for FIS planner. The FIS system was initially generated using heuristic rules. Once this model was ready, the fuzzy parameters were optimized using a Genetic Algorithm. Three sample problems were created and the quality of solutions generated by FIS was used as the fitness function of the GA. The GA tried to optimize the distance from the closest obstacle, total path length and the sharpest turn at any time in the journey of the robot. The resulting FIS was easily able to plan the path of the robot. We tested the algorithm on various complex and simple paths. All paths generated were optimal in terms of path length and smoothness. The robot was easily able to escape a variety of obstacles and reach the goal in an optimal manner.*

Keywords: *Path Planning, Robotics, Fuzzy Inference System, A* Algorithm, Genetic Algorithm, Heuristics, Probabilistic Fitness, Hierarchical Algorithms.*

1. Introduction

Robotics is a highly multi-disciplinary field that incorporates inputs from wireless systems, networks, cognition, image processing, AI, electrical, electronics and other related fields (Lima and Custodio 2005). The highly multi-disciplinary nature makes it an exciting playground for people from various fields to collaborate and contribute. The whole problem of robotics include taking input from sensors, making of robotic world map, path planning, robot control (Lee and Chiu 2009), multi-robot coordination, high-end planning, etc (Ge and Lewis 2006). The application of AI and Soft Computing techniques in the recent years deserves a special mention.

Path Planning (Kavraki et al 1996) is a specific problem in case of robots where we are given a map of the world. Through this we can come to know about the various paths and obstacles. The problem is to compute a path for the robot that can guide it to reach a specific goal starting from a specific position. Using this path the robot can reach its goal without colliding from any of the obstacles. The problem is usually studied under two separate headings. These are path planning in a static environment and path planning in a dynamic environment. In static environment the obstacles are static and do not change their position w.r.t. time. On the other hand, in

dynamic path planning the position of obstacles may change with time. A path planning algorithm must ensure that if a solution is possible, it is found and returned. This is called the completeness of the algorithm (Bohlin and Kaviraki 2000). It must also ensure that the algorithm gives its result within the specified amount of time (Kala et al 2009).

The problem of path planning takes its input a map. A robotic map is a representation of the world of the robot (Lozano and Wesley 1979). The map depicts the traversable path, obstacles, surface and conveys other information. Various types of paths may be drawn depending upon the problem and solution requirements. Some of the commonly used maps include topological maps (Thrun 1998), Voronoi maps (Castejon et al 2005; Sud 2008), hybrid maps, etc. The map is built using the results of the various sensors along with the output of the recognition systems (Ge and Lewis 2006).

Path planning usually provides output to the robotic control. This consists of a controller which is supposed to move the robot in the desired path. Various robot controllers have been designed. Some of them are built using the Adaptive Neuro-Fuzzy architecture (Ng and Trivedi 1998).

It was earlier shown by the authors that A* generates good results for the problem of path planning (Shukla, Tiwari and Kala 2008). However, the algorithm was found to be computationally very expensive. The A* algorithm also generates very sharp paths which the real robot would find it very difficult to follow. These are called the non-holonomic constraints of the robot. The motivation behind this work is to adapt A* algorithm to cater to these constraints. We do this with the application of probability based map representation (Kambhampati and Davis 1986).

The map in this paper has been modeled in a similar way to the quad tree approach as used by Kambhampati and Davis (1986). Here the top the nodes have high degree of uncertainty regarding the presence or absence of the obstacles. This uncertainty is measured in terms of *grayness* of the cell. A completely white cell denotes complete absence of obstacles from the region. On the other hand a completely black cell denotes the conformation of presence of obstacle in the cell. Grey denotes the intermediate values with the intensity denoting the probability of the cell being free from obstacles.

In practical problems, the map may be too large for the standard A* algorithm to solve. This problem is solved by making a hierarchical solution to the problem. The A* algorithm works on this probability based map. It tries to find a path of the smallest length that has a high probability of non-collision. The high probability factor ensures that it is feasible to follow this path and reach the goal without colliding with the obstacles. The path length factor ensures that the path generated is optimal to a good extent.

The A* algorithm gives the basic structure of the solution on a low level detailed map. This solution acts as a guide for the Fuzzy Inference System (FIS) based planner. The FIS planner generates solution in less time. The solutions follow the non-holonomic constraints. Also the solutions generated by the FIS avoid the robot getting too close to the obstacle. This is analogous to the motion of vehicles in everyday life. The FIS solution works on the detailed map and the solution generated by them is the final solution.

The initial fuzzy model used by the system was developed by experimentation and best of the understanding of the problem. Once this basic prototype was ready, GA was used to further optimize the model. There were 3 basic maps of ranging complexities that were used by the GA as benchmark problems. The GA was supposed to optimize the performance w.r.t. these maps. The performance was measured in terms of total path length, distance from nearest obstacle and the maximum turn angle. It may be seen that any good path would have the least length of the total path length, comfortable distance from nearest obstacle and least maximum turn angle at any time in the run on the path. GA fine tunes the generated model to convert it into the model that can be used for any general case.

The problem of path planning has been a very active area of research. The problem has seen numerous methods and means that cater to the needs of the problems. A class of algorithms uses the potential method approach to navigate a robot (Ge and Lewis 2006). In this approach, whenever the robot collides with a robot, a large potential is given. The potential increases if the robot moves too close to the obstacle. The aim is the minimization of the potential.

Pozna (2009) solved the problem using a potential field approach for obstacle avoidance. Other potential field methods include (Tsai and Chuang 2001). Hui and Pratihari (2009) gave a comparison between the Potential Field and the Soft Computing solutions. Various statistical approaches have also been used. This includes the

work of Jolly, Kumar and Vijaykumar who used Bezier Curve for path planning (2009). Goel (1994) solved the problem for dynamic obstacles using an adaptive strategy. Quad Tree (Kambhampati 1986), Mesh (Hwang et al 2003), Pyramid (Urdiales et al 1998) are representations that have been tried for better performance. Considerable work exists using the Soft Computing approaches especially Genetic Algorithms (Alvares, Caiti and Onken 2004; Juidette and Youlal 2000; Xiao, Michalewicz, and Zhang 1997; Lin, Michalewicz and Zhang 1994), A* Algorithms (Shukla, Kala and Tiwari 2008) and Artificial Neural Networks (Kala et al 2009). Shibata, Fukuda and Tanie (1993) used Fuzzy Logic for fitness evaluation of the paths generated. Various other approaches (Ordonez et al 2008; Cortes, Jaillet and Simeon 2008) have also been proposed.

Zhu and Latombe (1991) used the concepts of cell decomposition and hierarchal planning. Here they represented the cells in a similar concept of grayness denoting the obstacles. Urdylis et al (1998) used a multi-level probability based pyramid for solving the path planning problem. Hierarchical Planning can also be found in the work of Lai, Gen and Mamun (2007) and Shibata, Fukuda and Tanie (1993).

Along with the problem of path planning, the researchers have also studied the degrees of freedom and dimensionality as they have a deep impact on the solution. Jan, Chang and Parberry (2008) presented their work for solving in 3 degrees of freedom.

Chen and Chiang (2003) made an adaptive intelligent system and implemented it using a Neuro-Fuzzy Controller and Performance Evaluator. Their system explored new actions using GA and generated new rules. In the field of multi-robot systems, Carpin and Pagello (2009) used an approximation algorithm to solve the problem of robotic coordination using the space-time data structures. They showed a compromise between speed and quality. Pradhan, Parhi and Panda (2009) solved a similar problem for unknown environments using Fuzzy Logic. Peasgood, Clark and McPhee (2008) solved the multi-robot planning problem ensuring completeness using Spanning Trees. Hazon and Kaminka (2008) analyzed the completeness of the multi-robot coverage problem.

This paper is organized as follows. Section 2 gives the picture of the algorithm along with the discussion on hierarchical maps. The FIS planner is discussed in section 3. In section 4 we discuss the A* algorithm. Section 5 talks about the Genetic Optimizations. In section 6 we discuss the simulation model and the results. Section 7 gives the conclusions.

2. Algorithm Outline

In this section we give a general outline to the algorithm that we have developed for solving the problem of robotic path planning. The basic methodology is to use the A* algorithm for a higher end planning and FIS for the lower end planning. The FIS model is optimized by the use of GA. The general structure of the algorithm is given in figure 1.

The algorithm starts by taking as input the initial graph. This graph may be approximately built by the map building algorithm. This means that we do not certainly know whether obstacle lies at some cell or not (Kambhampati and Davis 1986). The A* algorithm runs on this map to generate a path P . The path P is a collection of points p_i such that p_1 is the cell cluster where the source node is found and p_N is the cell cluster where the goal node is found, N being the number of points in the A* solution.

These points are then used one after the other (other than the source) to act as guide for the Fuzzy Planner. As soon as the robot enters the region in which the goal cell is found, the next point in P becomes the goal and the robot has to move a step further. This goes on and on till the robot reaches the final block where the goal node is found. The FIS is used in every block for guiding the robot. After the last iteration, a FIS planner is used to make the robot reach the exact cell where the goal is located.

The training stage needs to be applied only once to generate the FIS. Afterwards the FIS may be used reputedly for all problems. First the initial FIS is generated and then the FIS parameters are optimized using GA. For this purpose benchmark maps were used. We discuss the various steps of the algorithm one by one.

2.1 Map

A map is the representation of the robotic world. The path planning algorithms use a map to get information about the obstacles and paths that are accessible. In this paper we have used a probabilistic approach to represent

a map. The map is represented in the form of grids of variable sizes. Each grid is marked with a color from white to black through grey. The color denotes the probability of the obstacles lying in that region. White means presence of no obstacle and black means a confirmed presence of obstacle. The grids are converted into a graph before running the A* algorithm. In the graph each vertex represents grids. All grids that are accessible by other grids (irrespective of presence or absence of obstacles) are marked as edges. One such representation of the map is given in figure 2.

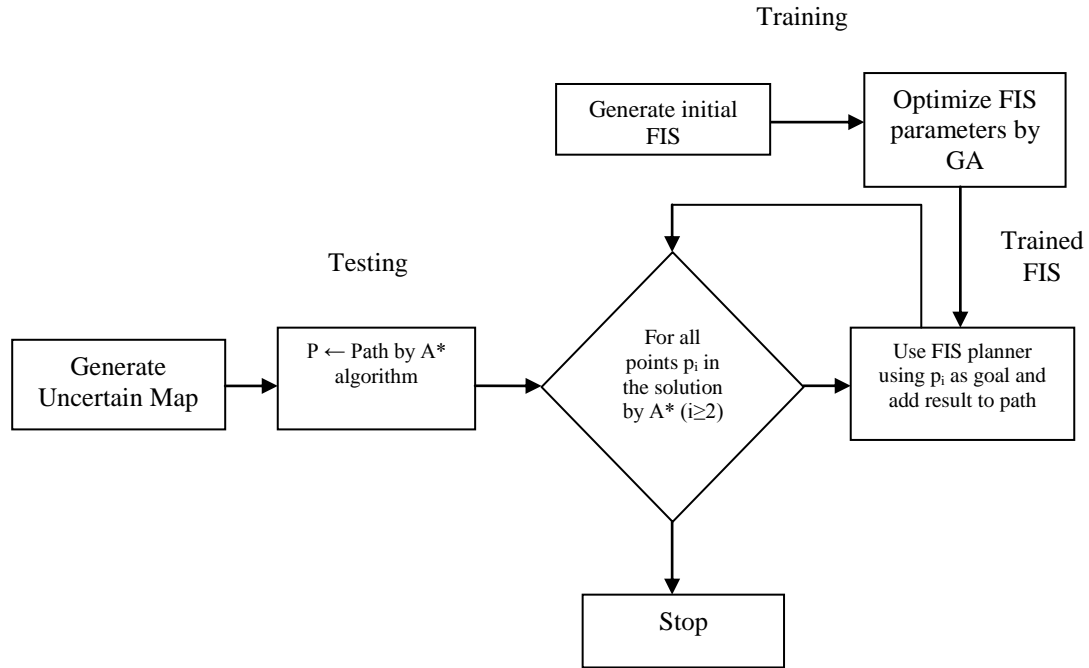


Fig 1: The whole algorithm

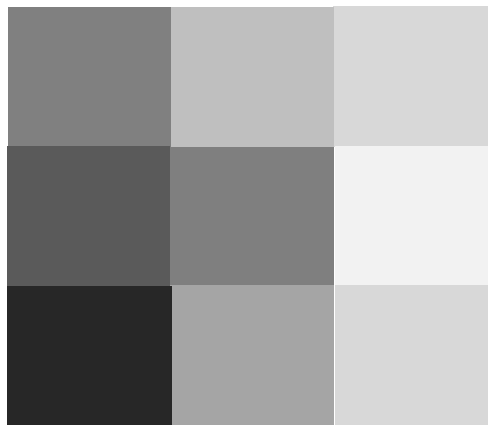


Fig 2: The map at any general point of time

The grayness is the measure of the number of obstacles in the cell. The grayness of any cell c may be calculated by using equation (1).

$$Grey(c) = 1 - \frac{\text{Total area covered by obstacles}}{\text{Total area of the cell}} \quad (1)$$

Suppose the whole map is built on a unit map consisting of some unit cells. The formula given by (1) in such a case converts into (2).

$$Grey(c) = 1 - \frac{\text{Total unit cells occupied by obstacles}}{\text{Total unit cells covered by } c} \quad (2)$$

Grayness of any cell lies between 0 and 1 and hence denotes the probability of collision of the robot in that cell. The probability based map is used only by the A* algorithm. The FIS planner uses the grid map where each grid is of unit size. The probability of the occurrence of obstacles in this grid is either 0 or 1.

The graph may be generated by decomposition of the probability based map. The map hence represents a two level hierarchy. The A* algorithm runs at the first level and the FIS planner at the second level. The first level is the abstract level and the second level is the detailed level. A graph at the first level consists of a number of grids of the second level. Let each grid at the second level consist of $\alpha \times \alpha$ grids of first level, where α is a parameter of the algorithm. If we increase α , the number of grids at the first level would decrease and vice versa. This is shown in figure 3.

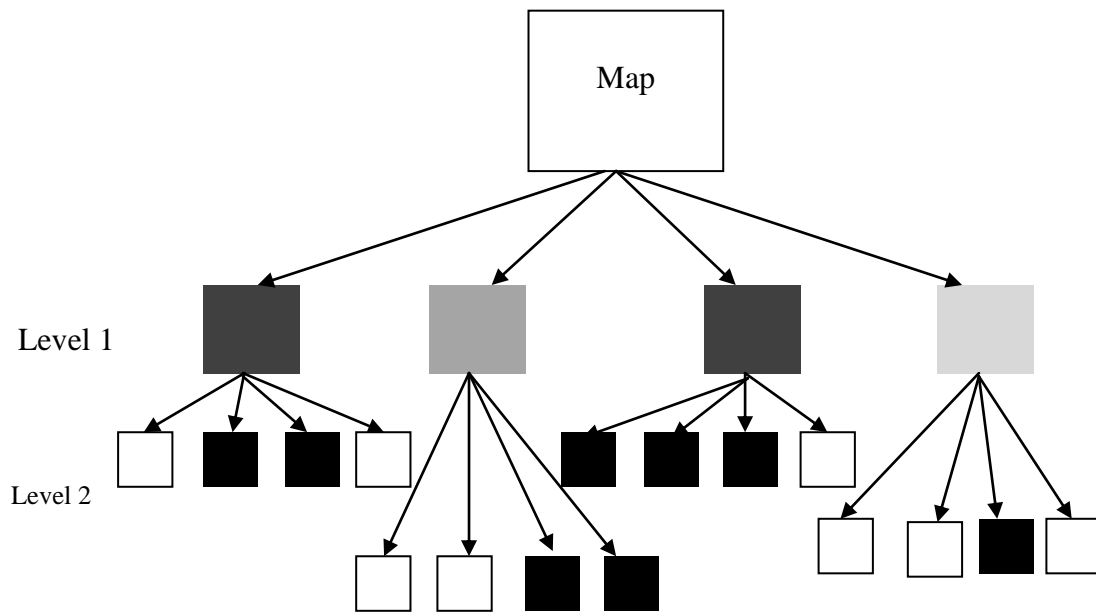


Fig 3: The 2 level hierarchy in map

2.2 The A* Guidance

The A* algorithm acts as a guide for the FIS. In this section we discuss this relation between the A* and FIS algorithm. The A* algorithm returns a set of points p_i at the first level that lead us to the goal. For the sake of convenience, we denote any point by (x_i, y_i) where x and y are the coordinates of the mid-point of the region covered by this point comprising of the level 2 points. The source is a level 2 point located somewhere in the p_1 region. The algorithm first sets p_2 as the goal for the robot that is still situated at the start position. The robot moves towards p_2 with an aim to reach it. As soon as the robot exits the region in which p_1 is located and enters into the region where p_2 is located, the goal is changed to p_3 . Now the robot tries to move towards p_3 . The robot keeps moving in this manner. In general if it is at any point of time at some region (x_i, y_i) covered by p_i , it would have as its goal the point p_{i+1} . This mechanism of guiding the robot goes on till the robot enters the region of p_N . Now the actual goal guides the robot to complete the left journey. The concept of the level 1 and level 2 points is shown in figure 4.

Figure 5 shows the robotic guidance. The red line shows the solution generated by the A* algorithm. Here the robot starts from the source with the goal as P_2 . While it is at area P_3 , the goal is P_4 . As soon as the robot reaches the point A, the goal is changed to P_5 . This way the robot keeps moving.

3 Fuzzy Inference System Planner

The movement of the robot in the system is done by a FIS Planner. The initial FIS was generated by hit and trial method. The FIS is supposed to guide the robot to reach the goal position. The FIS tries to find out the most optimal next move of the robot.

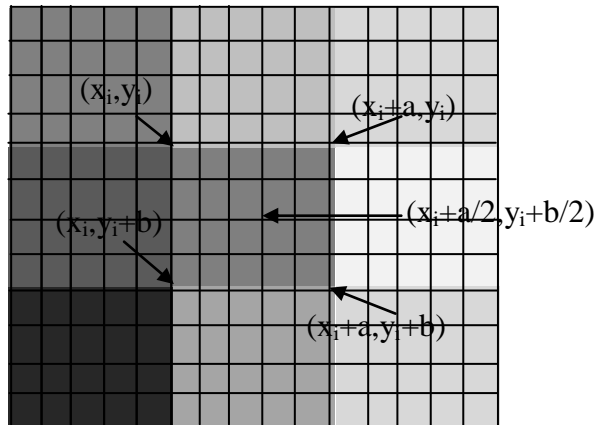


Fig 4: The formation of layer 2 grid from layer 1 points

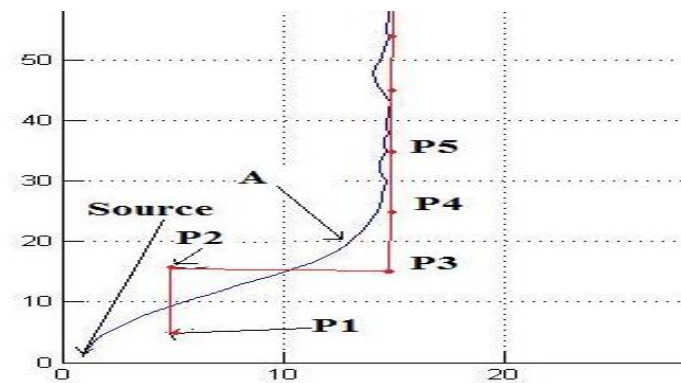


Fig 5: The robotic guidance

3.1 Inputs and Outputs

The FIS takes 4 inputs. There are angle to goal (α), distance from goal (d_g), distance from obstacle (d_o) and turn to avoid obstacle (t_o).

The angle to goal is the angle (α , measured along with sign) that the robot must turn in order to face the goal. This is measured by taking the difference in current angle of the obstacle (ϕ) and the angle of the robot (θ). The result is always between -180 degrees and 180 degrees. This is shown in figure 6.

The distance from goal (d_g) is the distance between the robot and the goal position. This distance is normalized to lie between 0 and 1 by multiplying by a constant. Similarly the distance from obstacle (d_o) is the distance between the robot and the nearest obstacle found in the direction in which the robot is currently moving. This is also normalized to lie between 0 and 1.

The turn to avoid obstacle angle (t_o) is a discrete input that is either 'left', 'no' or 'right'. These stand for counter-clockwise turn, no turn and clockwise turn respectively. This parameter represents the turn that the robot must make in order to avoid the closest obstacle. This input is measured by measuring the distance between the robot and the obstacle at three different angles. The first distance is the distance between the obstacle and the robot measured at the angle at which the robot is facing (a). The second distance is the same distance measured at an angle of $d\theta$ more (c). The third distance is measured at an angle $d\theta$ less (b). These three distances are given in figure 7.

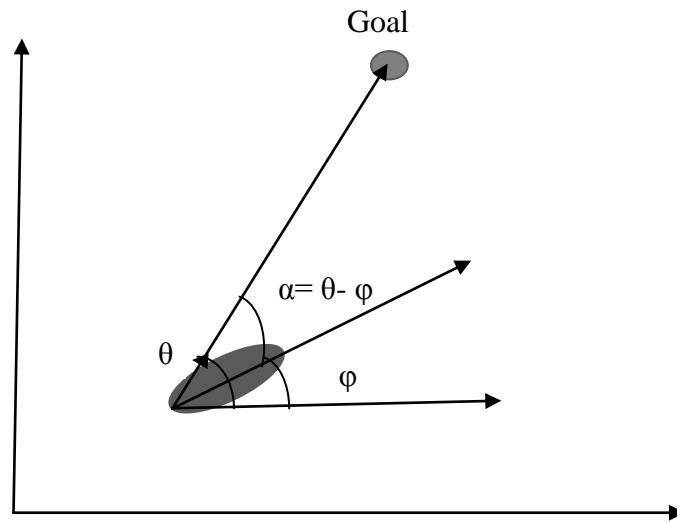


Figure 6: The angle to goal

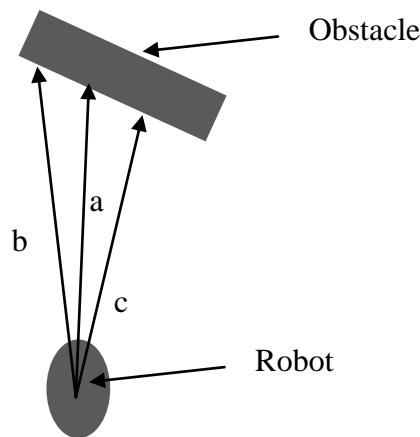


Fig 7: The determination of turn to avoid obstacle

Various cases are now possible. The first case is $c > b$. This means that the obstacle was turned in such a way that turning in the clockwise direction made it even further. In this case the preferred turn is clockwise with an output of 'right'. The second case is $b > c$. This means that the obstacle was turned in such a way that turning in the anti-clockwise direction made it even further. In this case the preferred turn is anti-clockwise with an output of 'left'. The third case is $b = c$. This is the case when the robot is vertically ahead of the robot. In such a case we follow a 'left preferred' rule and take a 'left' turn.

There is a single output that measures the angle (β) that the robot should turn, along with direction. The membership functions of the different inputs and outputs are given in figure 8.

3.2 Rules

Rules are the driving force for the FIS. Based on the inputs, we frame rules for the FIS to follow. The rules relate the inputs to the outputs. Each rule has a weight attached to it. Further some inputs have been applied with the not operator as well. All this makes it possible to frame the rules based on the system understanding.

The rules can be classified into two major categories. The first category of rules tries to drive the robot towards the goal. The second category of rules tries to save the robot from obstacles. If an obstacle is *very near*, the

second category of rules become very dominant. 11 rules are identified. These are given in figure 9. The numbers in brackets denote the weights.

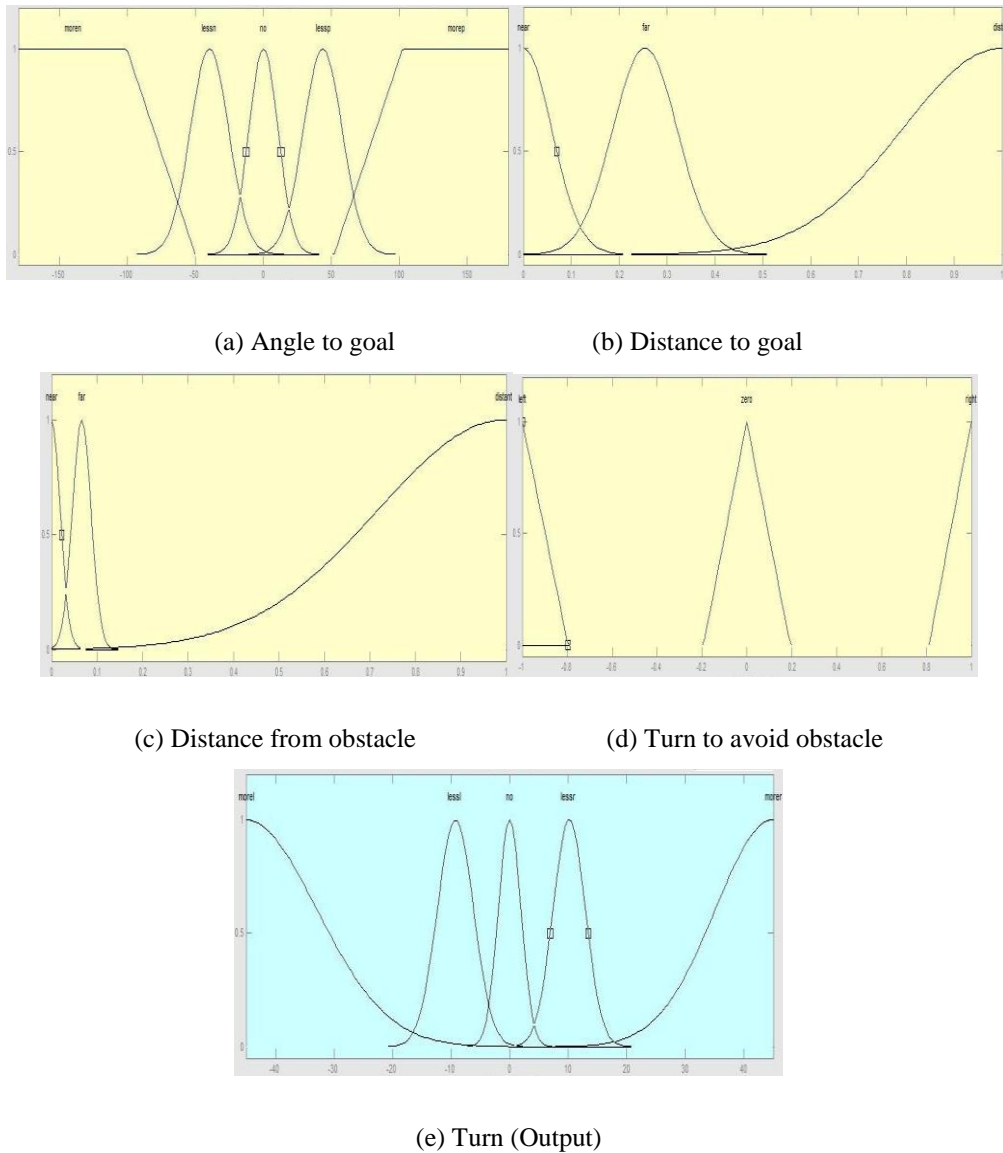


Fig 8: The membership functions

- Rule1: If (α is less_positive) and (d_o is not near) then (β is less_right) (1)
 Rule2: If (α is zero) and (d_o is not near) then (β is no_turn) (1)
 Rule3: If (α is less_negative) and (d_o is not near) then (β is less_left) (1)
 Rule4: If (α is more_positive) and (d_o is not near) then (β is more_right) (1)
 Rule5: If (α is more_negative) and (d_o is not near) then (β is more_left) (1)
 Rule6: If (d_o is near) and (t_o is left) then (β is more_right) (1)
 Rule7: If (d_o is near) and (t_o is right) then (β is more_left) (1)
 Rule8: If (d_o is far) and (t_o is left) then (β is less_right) (1)
 Rule9: If (d_o is far) and (t_o is right) then (β is less_left) (1)
 Rule10: If (α is more_positive) and (d_o is near) and (t_o is no_turn) then (β is less_right) (0.5)
 Rule11: If (α is more_negative) and (d_o is near) and (t_o is no_turn) then (β is less_left) (0.5)

Fig 9: The FIS rules

4 A* Algorithm

The A* algorithm is responsible for the high end planning of the robot. A* algorithm generates very efficient solutions in robotic path planning problem. In this algorithm, we have used a probability based A* algorithm. The reason for this is that the A* algorithm runs at a level, where the exact information about the obstacles is unknown. The A* algorithm tries to find a solution in this probability based map. The algorithm is supposed to minimize the path length and at the same time maximize the probability of reaching the goal from this path.

The A* uses the cost function for deciding the goodness of the solution. The better solutions have lower costs. Hence the approach is generally to find smaller costs and expand the associated nodes further. This algorithm is based on probability that is denoted by the probability of finding obstacle in the cell. Hence each path we traverse has some probability of success associated with it. This probability for a path is given by equation (3).

$$Grey(P) = \prod_i Grey(p_i) \quad (3)$$

Here p_i are the consecutive nodes that make up the total path P .

The other costs that the algorithm uses are Heuristic Cost $h(n)$ and the Historical Cost $g(n)$. For the A*, the total cost $f(n)$ is given by the sum of Heuristic Cost $h(n)$ and Historical Cost $g(n)$. In this algorithm we use the historic cost as distance of the center of the node from the source and the heuristic cost as the cost of the center of node to the goal.

The total fitness $C(n)$ in this case is the probability based total cost. This is given by (4)

$$C(n) = f(n) * Grey(P) + (1 - Grey(P)) \quad (4)$$

Here P is the path of traversal till node n .
 $f(n)$ has been normalized to lie between 0 and 1.

It may be noted here that equation (5) has been derived keeping in mind the following points

- If $Grey(P)$ is 0, it means that the path is not feasible. The fitness in this case must have the maximum possible value i.e. 1
- If $Grey(P)$ is 1, it means that the path is fully feasible. The fitness in this case must generalize to the normal total cost value i.e. $f(n)$
- All other cases are intermediate

The graph of this function is as shown in figure 10.

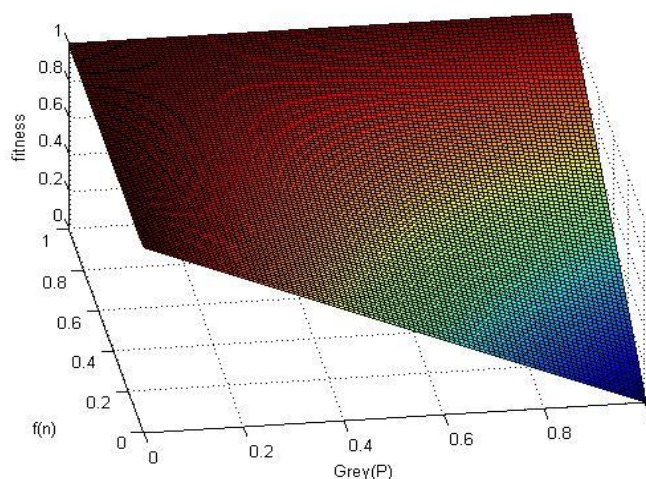


Fig 10: The plot of fitness function

The grayness plays a very vital role in deciding the performance of the algorithm. If the A* algorithm tries to maximize the probability too much, it may result in the suboptimal values being selected, because of the fact

they lead to higher probability. This would result in the robot opting for longer paths to avoid any possible obstacle. Based on these ideas, we try to modify equation (5) by introducing a parameter β that controls the effect of the grayness in the fitness function. If the value of β is kept as 0, the A* algorithm completely discards the effect of grayness and converts into a normal un-probabilistic A* algorithm. The modified equation (4) is given by equation (5).

$$C(n) = f(n) * \text{Grey}^{\beta}(P) + (1 - \text{Grey}^{\beta}(P)) \quad (5)$$

Here $\text{Grey}^{\beta}(P)$ is given by equation (6)

$$\text{Grey}^{\beta}(P) = \begin{cases} 1, & \text{if } \text{Grey}(P) > \beta \\ \text{Grey}(P) & \text{otherwise} \end{cases} \quad (6)$$

The fitness function for $\beta=0.6$ is given in figure 11

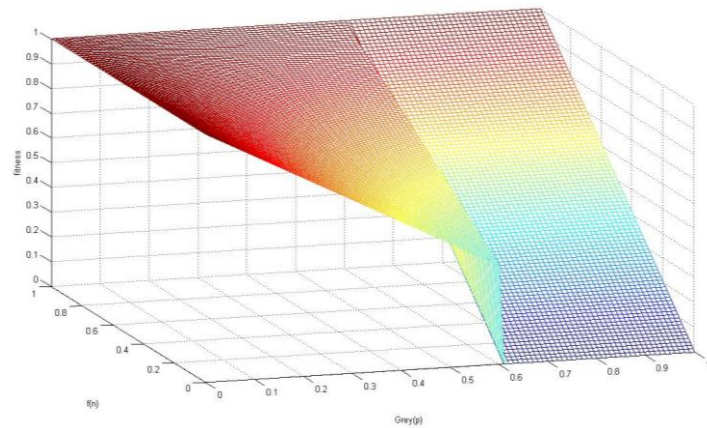


Fig 11: The plot of modified fitness function

5 Genetic Optimizations

The Fuzzy model discussed in section 3 was an initial fuzzy model that was generated. The parameters of this model were decided by trial and error. In order to make this a scalable system, further optimizations were necessary. This was done by means of GA. GA was supposed to optimize the fuzzy parameters (parameters of all membership functions used) for most optimal planning of the robotic path. There were a total of 32 fuzzy parameters that were optimized by the GA.

For this problem, we first created 3 maps that acted as benchmark maps for the GA. The GA was supposed to optimize the performance of the system against these maps. The first map was a simple map with no obstacles. The second map had single obstacles on the way from source to goal. The robot was supposed to avoid this path. The third map had many obstacles and the robot was supposed to find its way out of them. These maps are given in figure 12.

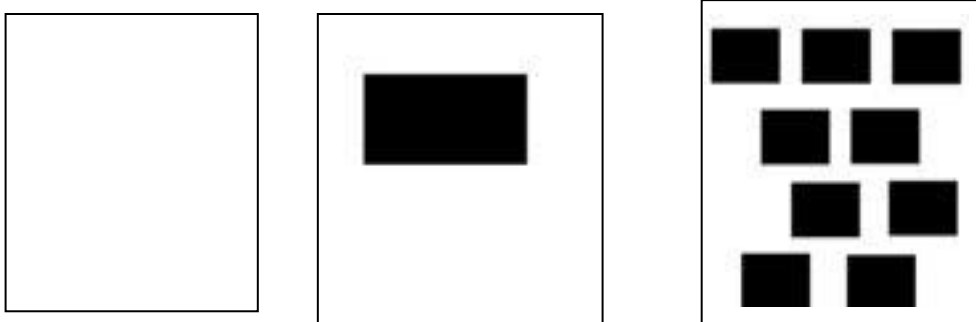


Fig 12: Benchmark maps for GA (a) No obstacle (b) Single obstacle (c) Many Obstacles

The fitness function for any of the map i tried to optimize three objectives (i) The total path length (L_i) (ii) The maximum turn taken any time in the path (T_i) (iii) Distance from the closest obstacle anytime in the run (O_i). All these were normalized to lie on a scale of 0 to 1. The total fitness for any map i may hence be given by (7)

$$F_i = L_i * (1-O_i) * T_i \quad (7)$$

The fitness F_i for any solution hence lies between 0 and 1. 1 is the maximum fitness a solution can attain. If the robot at any time moves out of the map, or collides with an obstacle, we assign it a fitness value of 0. The GA would naturally result in deletion of such solutions in the course of generations. In this manner we handle infeasible solutions in GA.

The total fitness (F) of any individual in GA is the sum of its score or fitness in all these three maps. This is given by (8). The total fitness can be anywhere between 0 and 3.

$$F = F_1 + F_2 + F_3 \quad (8)$$

6 Simulation and Results

In order to test the working of the algorithm, we made a simulation engine of ourselves. Every attempt was made to ensure that the simulation engine behaves in a way similar to actual robot. This would ensure that the algorithm can be easily deployed on a real robot for the purpose of path planning. All simulations were done on a 2.0 GHz dual core system with 1 GB RAM. The initial graph was taken as an input in form of an image. The image depicted the obstacles as black regions and the path as the white region.

The first major task was the Genetic Optimization of the FIS. Then this optimized model was implemented and tried on the benchmark problems. The system was then tried on numerous maps with varying obstacles. These are given in the next sub-sections.

6.1 Genetic Optimizations

The purpose of the GA was to find out the exact parameter values for the FIS. 32 such parameters were identified that needed optimizations. The Matlab GA toolkit was applied for the optimization purposes. The GA search space consisted of the region around the value chosen by the hit and trial method of the 32 parameters. We restricted the search to 10% of this value on both sides. This means if the value of any parameter was x , the GA was supposed to optimize it in the search region of $x-0.1*L$ to $x+0.1*L$ where L is the total range of values that x can take. It is natural that on the basis of rules framed, the solution was not likely to be present in any other region. This provided ample of space for GA to locate the global minima and at the same time making the space finite to search for possible solutions.

The population was represented by the double vector mechanism. The population size was fixed to 50. Rank based fitness scaling was used. Stochastic Uniform selection was used. The crossover rate was 0.8 with elite count as 2. Gaussian Mutation function was used with a scale and spread of 1 each. The GA was made to run over 100 generations. It took about 1 hr 15 mins for the GA to complete the generations. The fitness curve of GA showing the mean and best fitness is given in figure 13. The final fitness of 0.04850 was achieved by the GA.

6.2 Benchmark Maps

The first tests were applied at the benchmark problems. This was an attempt to see the behavior of the algorithm at the benchmark problems. Since these benchmark problems were applied on low resolution graph of size 100X100, there was no need to run the A* algorithm. Direct FIS planner was used. The maps are shown in figure 12. The path traced by the algorithm after optimization is given in figure 14. Figure 15 shows the same problem being solved by application of A* algorithm alone. In all cases the source is the top left corner of the map and the goal is the bottom right corner of the map.

The solutions generated by the algorithm were all smooth so that the robot can be easily turned as per requirements. They were all of optimal length. In each case the robot was easily able to steer its way by avoiding obstacles and reach the goal node.

In all the cases the robot was initially facing at the direction of the X-axis and not towards the goal. This is the reason why we see a smooth transition in path and angle at the starting points in the graph. The solutions generated by A* algorithm however do not reveal this. These solutions assume the robot would somehow turn towards the angle of the goal and then it would start moving in a straight line towards it.

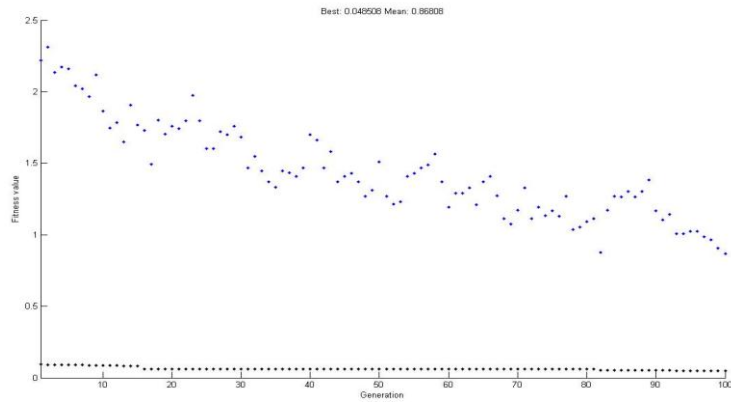
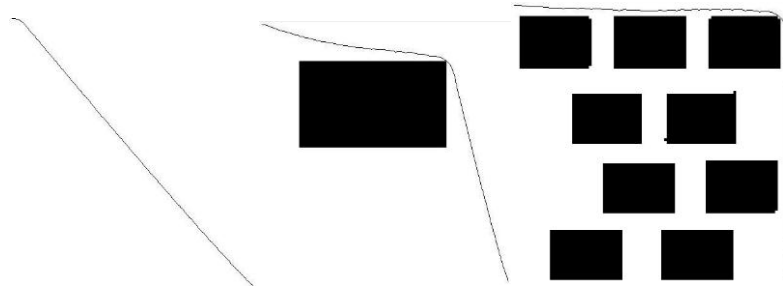
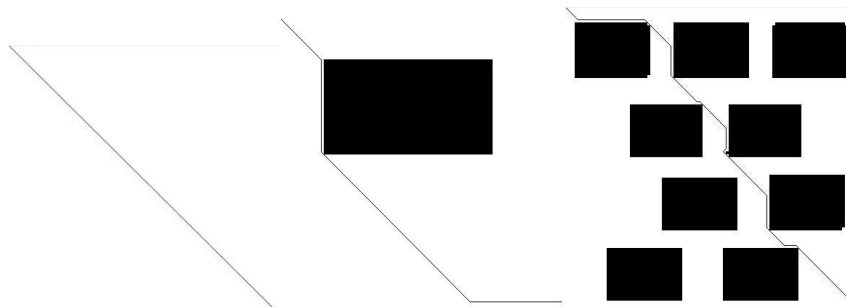


Fig 13: The mean and best fitness in GA



(a) Map 1 (b) Map 2 (c) Map 3
Fig 14: The path traced by algorithm for benchmark maps



(a) Map 1 (b) Map 2 (c) Map 3
Fig 15: The path traced by standard A* algorithm for benchmark maps

Figure 14(b) shows another very interesting solution; where the robot made a smooth transition and started moving in a manner to just avoid the obstacle. When the obstacle ended, it again smoothly changed its direction. The nearness of the obstacle avoided the undue long tracing of path and the turns were smooth enough for the robot to be taken. Similar inferences may be made from figure 14(c).

The very sharp turns present in figure 15(b) and 15(c) clearly show that these solutions are not practical and further they cannot be easily converted to smoother paths as well. This exposes the weaknesses of A* algorithm.

Further looking at figure 14(c) and 15(c), we see that our algorithm guided the robot from the top of the obstacle (remember we adopted a 'left preferred' approach). The A* algorithm on the contrary guided the robot from the

middle of obstacle. It may be argued that the unequal length may not be optimal. We will see later that the guidance by the A* is responsible for the path length and it divides the problem in such a way that the most optimal path is selected in most of the cases.

6.3 More Maps

In order to fully test the behavior of the algorithm, we tested the algorithm against 3 more maps. This time the maps were of larger size of 1000X1000. Many obstacles were placed in between the source and the goal. The robot was supposed to reach the goal from the source. The top left corner is the source and bottom right corner is the goal. In all the cases, the source was fixed as the top left corner and the goal was fixed as the bottom right corner.

The first test case was the obstacle avoidance test. Here we placed numerous small and big obstacles that were kept on the path of the robot. We observed that the robot was easily able to guide its way towards the goal. It could smoothly manage to overcome the numerous obstacles of all sizes and shapes that were on its way. The path traversed by the robot was quite optimal. The map and the path traced by the algorithm is given in figure 16(a). The initial path given by the A* algorithm while working at level 1 map is given in figure 16(b). The path traced only by the application of A* algorithm is given in figure 16(c) and only by the Fuzzy planner is given in figure 16(d).

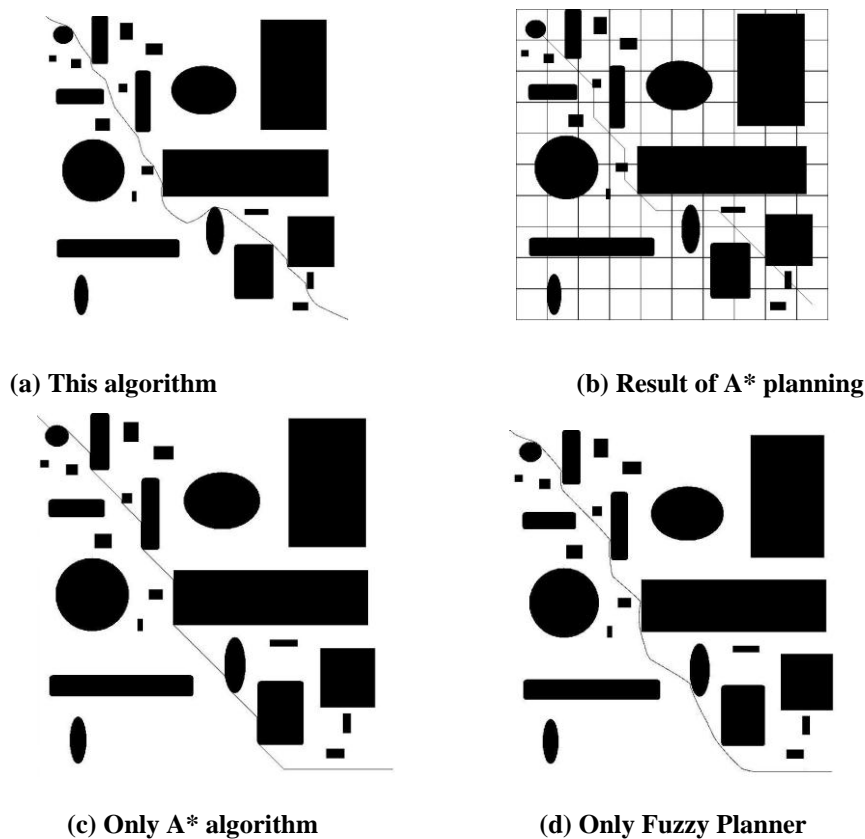


Fig 16: The obstacle avoidance test case

The second test case applied was of scattered obstacles. In this many small obstacles of abrupt lengths were placed between the source and the goal. In this case as well, the algorithm could smoothly guide the robot. The total path length was not optimal in this case, but was optimal enough considering the non-holonomic constraints. The extra path was a result of the probabilistic approach of the A* algorithm that wanted to maximize the certainty. The map and the path traced by the algorithm is given in figure 17(a). The initial path given by the A* algorithm is given in figure 17(b). The path traced only by the application of A* algorithm is given in figure 17(c) and only by the Fuzzy planner is given in figure 17(d).

The third test case applied was of a simple maze like situation. A complex map was given. The robot was supposed to find its way out. In this case as well the robot was able to guide itself out. It may be noted that the maze considered was kept simple enough for the fuzzy planner to make out. In case we had used a difficult map,

the fuzzy planner would have ended up in a collision. The map and the path traced by the algorithm is given in figure 18(a). The initial path given by the A* algorithm is given in figure 18(b). Here also it tried to maximize the probability. The path traced only by the application of A* algorithm is given in figure 18(c) and only by the Fuzzy planner is given in figure 18(d).

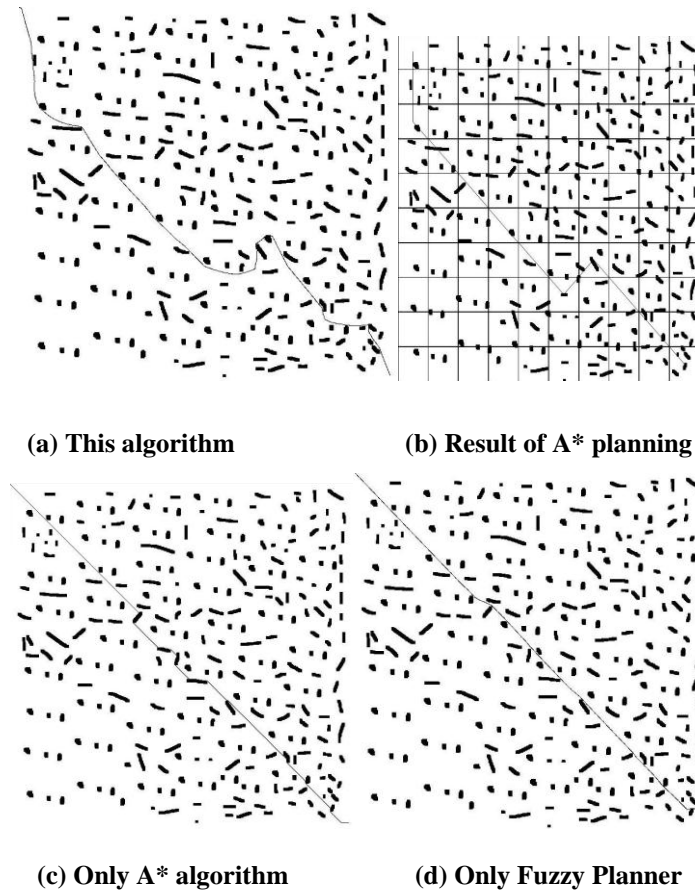


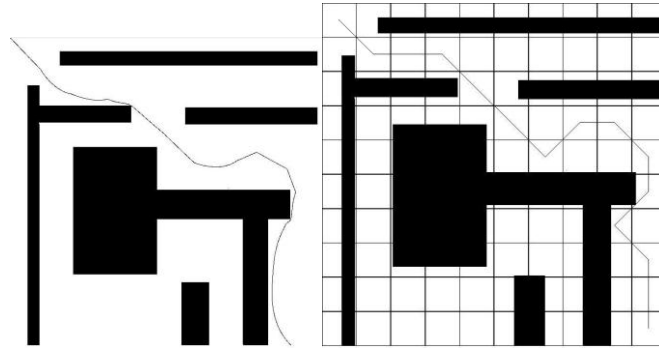
Fig 17: The scattered obstacle test case

6.4 Effect of Change in Grid Size

In this problem we had introduced a 2 level hierarchical map. The 2nd level map was a detailed version of the 1st level map. The 1st level was probabilistic in nature. Here various nodes of level 2 had been clubbed to form a single grid or cell. The size of this grid (α) decides the working of the algorithm. If α is very small almost entire graph would be available at the 1st level. The solution would be predominantly A* in nature. If the size is too large, there would be nothing considerable at the 1st level. In that case the solution would be predominantly of the nature of Fuzzy Planner. In all other cases, the solution would be a mixture of A* and Fuzzy planner characteristics.

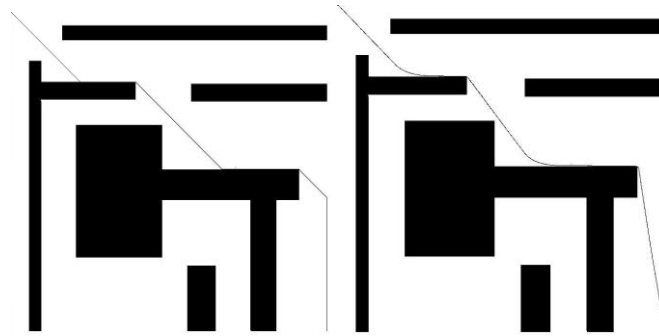
The probability based fitness used in the A* algorithm is the other factor that changes with the change of α . As we increase α , the probability keeps getting vague due to the higher grid size. The A* algorithm tries to find paths that have high probability of reaching to the goal. This in turn ensures that under any circumstances, the fuzzy planner would be able to reach the goal position with the maximum level of certainty. However, the probability has an undue effect on the path length. In order to increase the path probability, the length is compromised. This in turn causes the total path length traversed by the robot to increase.

We studied this effect into the various maps that we had used. The path traced by the robot for one such map is given in figure 19.



(a) This algorithm

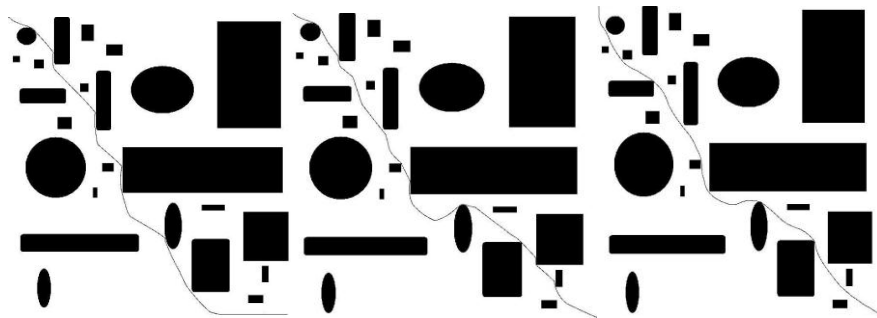
(b) Result of A* planning



(c) Only A* algorithm

(d) Only Fuzzy Planner

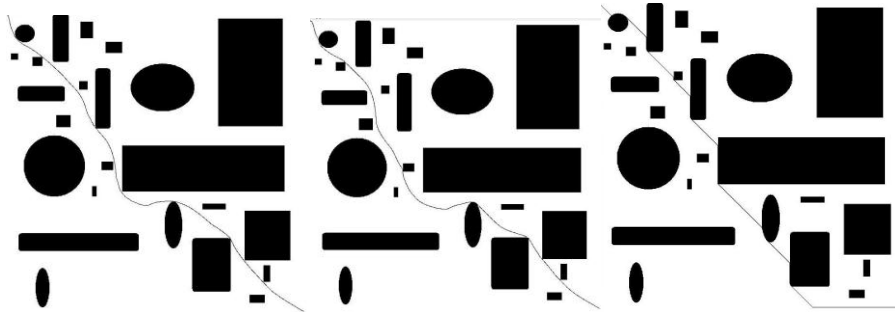
Fig 18: The simple maze test case



(a) $\alpha = 1000$

(b) $\alpha = 100$

(c) $\alpha = 20$



(e) $\alpha = 10$

(f) $\alpha = 5$

(g) $\alpha = 1$

Fig 19: The path traced by robot for various values of α

6.5 Effect of Change of Grayness Parameter

The other parameter that we try to change is β . This parameter was discussed in Section 4. As per the discussion it is clear as this parameter would increase, the conventional non-probabilistic behavior would get predominant in the behavior of the algorithm. We studied the change of this parameter into numerous maps. Figure 20 shows the results on the same graph that was used in our discussion in section 6.4. It may be seen that the algorithm failed for $\beta=0$. This is because the A* algorithm returned a straight path from source to goal which had very less probability. The other inputs could not produce a change in the output of the A* algorithm. It may be observed here that change of β tries to make a change in A* algorithm result. As a result, the change in path would be discrete rather than continuous. Whenever there is a change in path of the A* algorithm result, a discrete change is reflected. This depends upon the probability conversion and the grid size (α). The experiments were conducted at a large grid size. In smaller grids the change appears to be more continuous.

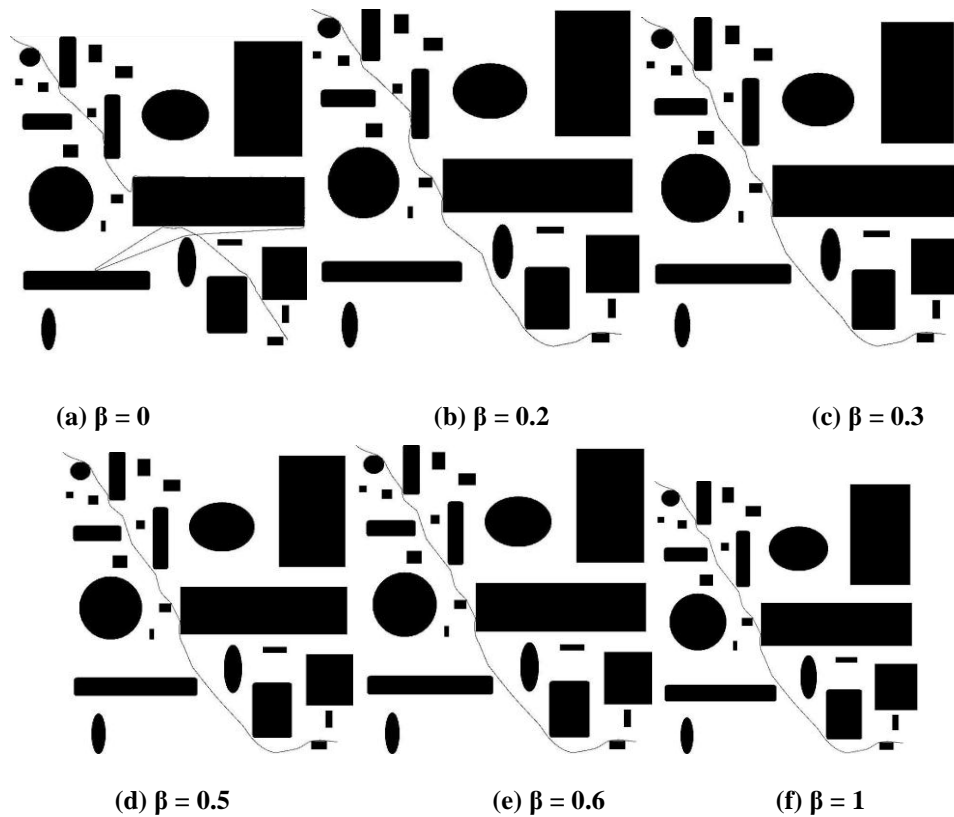


Fig 20: The path traced by robot for various values of β

6.6 Discussion of interaction between parameters:

It may easily be seen that the total path is affected by 3 factors (i) the contribution of the Fuzzy Planner that makes the path smooth at the same time reducing time of algorithm. It however may result in a longer path or the failure in finding path in case of complex maps (ii) the contribution of the A* algorithm in reducing the path length (α), which can solve very complex maps with most optimal path length at the cost of computational time (iii) The contribution of the A* to maximize the probability of the path (β), which usually would increase the path length.

The combined effect of the change in values of α and β would reveal the generation of unique paths. This makes the task of planning using the proposed algorithm very flexible, where different parameters may be set as per the problem. These would result in different kinds of paths with varying path lengths and smoothness. Based on the results of figure 16 and 17, it may be seen that we can generate all kinds of paths between A* algorithm, Fuzzy planner and probability based approach by the adjustment of these parameters. The flexibility however puts the constraint that these parameters need to be judiciously set, so as to attain optimal results. The parameters have a strong dependence on numerous factors like map, path simplicity, robot design, total map size, etc. This eliminates the possibility of constant values of these parameters for different scenarios and maps. The task of parameter setting for α and β may be done by considering the same factors. Very simple maps with fewer turns

may have more A* contribution. The presence of multiple objects in the optimal path may require a lot of Fuzzy planning to escape from the variety of objects.

7 Conclusions

In this paper we have proposed a method to solve the problem of path planning using a combination of the A* algorithm and Fuzzy Planning. We tested the algorithm for various test cases. In all the test cases we observed that the algorithm was able to find the correct solution. The solutions generated by the algorithm were often close to optimal. They took relatively small times to solve for each of the map presented. Further, the solutions obeyed the non-holonomic constraints and the path generated by the algorithm can be easily used by any robotic controller to move the robot physically. In this paper we had further used a probabilistic approach in the map representation. The map was implemented at two levels for the A* algorithm and the fuzzy planner. The FIS was genetically optimized for performance.

The results convey a very unique relation between the working of the A* algorithm and the FIS planner. The A* algorithm works over a probabilistic map trying to optimize the path length and at the same time making the probability of reaching the goal high. The FIS was used primarily for giving smooth paths according to the non-holonomic constraints and ensuring a timely response to the system. The A* algorithm at one hand reduced the total path length by selecting the solutions that have less total length. At the same time the increase of probability resulted in selection of longer paths at some positions.

We further solved each of the path with all three algorithms (i) this algorithm (ii) only A* algorithm and (iii) only fuzzy planner. From these results it may be seen that this algorithm is a unique mix of the other two algorithms. It tries to combine the best features of path length and smoothness in the solution it generates.

The contribution of each of the A* algorithm and Fuzzy Planner may be varied by changing the grid size (α) and the probability factor (β). This would make the algorithm behave more like one or the other. If the grid size is very small, the algorithm would be primarily A* in nature. This may induce very sharp paths. Further if the grid size is very large, the resulting algorithm would be dominated by the Fuzzy planner properties. It may not be able to solve complex maze like paths. Similarly if β is very large, the total path length might be more due to the effort of A* to optimize the path length. Reducing β may result in shorter paths, but at the same time the robot may fail to reach the goal or may get obstructed from the path as the path it is trying to follow may have low probability.

Another characteristic feature is the dynamic nature of the algorithm. The Fuzzy Planner can run in a very dynamic environment. Any change in the graph at any time can be easily adapted in real times. This further makes it possible to use the algorithm in dynamic environments.

In the proposed algorithm GA was used to optimize the parameters of the FIS. This led to a better performance of the FIS in escaping the obstacles and moving towards the goal. FIS represents the robotic behavior that is not map-specific. The GA tunes the behavior in such a manner that the robot learns to take optimal moves in different kinds of scenarios. This results in optimal movement of the robot in different kinds of map with simple or complex-shaped obstacles.

The experimentation done in this paper was mainly on static environment. The algorithm may be further adapted for modeling mobile obstacles in a space time graph. This would make an effective dynamic algorithm. A further work to decide effective grid size (α) and probability factor (β) needs to be done. Formulation of more benchmark problems covering all cases that a robot may face in real life may also be done. Further the FIS rules may be more intensively studied and modified in the future. The algorithm is yet to be studied in a way that balances or tunes the effects of probability of the path, the A* algorithm and the fuzzy planner in the entire path.

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