International Journal of Pure and Applied Mathematics
Volume 117 No. 15 2017, 983-989
ISSN: 1311-8080 (printed version); ISSN: 1314-3395 (on-line version)
url: http://www.ijpam.eu
Special Issue

ijpam.eu

STRATEGY FOR COLLISION FREE ROBOT PATH PLANNING IN STATIC AND DYNAMIC ENVIRONMENT USING GENETIC ALGORITHM

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Abstract

In this paper, a methodology developed to probe navigation path to work on static and dynamic environments by making amends to the incorporation of the obstacles using Genetic Algorithm principle with Selection, Crossover and Mutation operators are used to make the algorithm operative. The capacity to adapt to the environment changes is made effective by adopting different methods. The variations in the number of obstacles and the limitations applied to the robotic movements at each instance helped to arrive at efficient results. The test result helps us to perceive the direct proportionality relation that exists between the search space and the complexity of the environment.

Keywords- Path planning, Genetic Algorithm, obstacle avoidance, collision free.

Introduction:

The Darwin's Theory of Evolution served as an inspiration to the discovery of Genetic Algorithm. Genetic Algorithm is a method to solve both constrained and unconstrained optimization problems. In this approach, we establish a pattern for the traversal of the robot to reach its target. Having known the obstacles involved and also to inure the Dynamic obstacles, strategic movements are used that helps for the same.

Navigation of the mobile robots is effected by the two main components: Localization and Path planning. The original position matching to the actual one in the environment is availed using localization. Planning aids in the identification of an optimized collision free path to the target position. Optimization problems emphasizes on heuristic based path planning approaches in the search space. Intensive Computation and the precarious behaviour of the classical methods [1] constitutes for its disadvantage. Classification or the efficiency test of the different methods that are already used is not the region of concentration. Instead, the efficacy strategies that will help arrive at better optimal results are brought to priority.

Research studies include Classical algorithms like cell decomposition[2], potential field[3] and also Meta heuristic algorithms[4] like Neural Network[5], Ant Colony Optimization (ACO)[5,6], Particle Swarm Optimization (PSO)[7,8], fuzzy logic[9,10] and Genetic Algorithm (GA)[11] and multi objective genetic algorithm[12]. Hybridization of the above algorithms[13]is also being employed to obtain the solution. This type of problem finds many applications in manufacturing, transportation and mobile systems. Genetic algorithm is robustand it has proved to be efficient when the search space is complex. In this method, the environment is a 2D-space grid environment. Different approaches are used to get the solution for 3D working space[14].

Path planning plays a vital role in robot motion planning. Given the workspace of the robot, its traversal from the source to target position establishes the path. The system that is to be proposed is bound to make use of an effective path planning algorithm that will bring together all the feasible paths from the initial and final positions.

In the work space that is used for traversal, it is exposed to have many obstacles which can be either static or dynamic. In the event of having static obstacles, prior knowledge about the obstacles is the elixir for the robot. This will abet in the navigation to the respective target position. The probability of the dynamic obstacle occurrence is to be handled on the traversal path of the robot. The inundate capacity to traverse across and produce an optimal path is the most essential element. User prompting dynamic generation is actuated in the environment as it is used for the testing phase. The appropriate co-ordinate positions for the block andtraversal operations are to be specified for the path discovery of the robot.

Backtracking is to be used only when the dynamic obstacle generation blocks the path traced. In order to trace a path avoiding the obstacles generated, the former served to be the solution. This contributes to the added advantage of reducing the processing time and it is proved to be cost effective.

RELATED WORK

Wang Jianguo et al.[15]proposed a method to overcome the drawbacks of traditional genetic algorithm such as prematurity and lower convergence speed they have come up with an idea of improved Genetic Algorithm. Population is initialized based on probability of a fast random search method. The Characteristics that differentiate the proposed GA from traditional is that a Deletion operator is introduced apart from which Elitist strategy is also being carried out. The workspace of the robots is discretized into grids. The results manifest that the algorithm is capable of adapting to the environmental changes. The computational complexity is considerably reduced which leads to faster convergence speed. Moreover the optimal path obtained is of shorter length.

Yanping Liu et al.[16] have projected a hybrid approach using artificial potential field and genetic algorithm for the purpose of planning the path of mobile robots in dynamic environment. Here the workspace of the robot is represented using grids. Then Genetic algorithm is applied to obtain an optimal path. After which they have exercised Artificial Potential Field algorithm to avoid obstacles and navigates from one intermediate node to another. Their conclusion results state that the algorithm avoids the obstacles effectively and their processing time has been reduced.

Environmental model:

Grid based environment are most popular models. In this method, the search space is divided into square cells. The position of the robot at any instant is denoted by their respective co-ordinates.

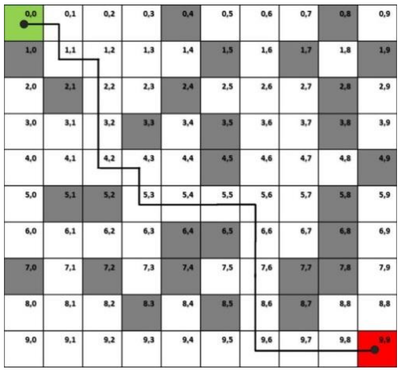

Figure 2.a. Grid representation of workspace

Individual path is obtained in terms of co-ordinates. The shaded regions are the obstacles and the rest denotes the free space of the search environment. Initially, a number of static obstacles are assigned at different coordinate positions [17]. The values in these positions are randomized. In addition to these, dynamic obstacles of varying sizes are introduced to test the robot's efficacy. Here, the starting position of the robot is (0, 0) and target position is (9, 9). For e.g. in fig.1 The path obtained isdenoted as{(0,0),(1,1),(2,2),(3,2),(4,2),(5,3),(5,4),(5,5),(5,6),(6,6),(7,6),(8,6),(9,6),(9,7),(9,8) and (9,9)}. The length of the above path is 16, which is the number of grids it traverses.

Population Initialization and Parameter Selection

The input to the problem is in the form of a matrix (i, j) with i rows and j columns. The algorithm's parameters[18] are population size (p), number of generations (n), obstacle size(s), crossover probability(c), mutation probability (m) [1]. In order to safeguard the initial population and enhance diversification, crossover probability and mutation probability are subjected to change. Each phase of the genetic algorithm [19] influence the optimal solution obtained at the end of the process. The source and destination for the robot are nothing but the start and end point of the matrix. It is expected that the path traversed by the robot should consider these constraints.

Fitness function and evolutionary operators:

Fitness function:

Fitness function is the significant one to select the candidate solution which will lead to the convergence for the solution space[2]. The fitness value of the individual determines the probability of the individual to be genetic to the next generation

F= (Ls + Ll)/2

Where Ls= length of shortest path; Ll= length of longest path in that particular generations respectively.

Evolutionary operators:

The employment of evolutionary operators such as Selection, Crossover, and Mutation helps us in the optimization and find out what could be the best outcome out of all the possible outcomes.

Truncation selection operator:

The next generation is created by selecting individuals from the existing population.The truncation operation chooses individuals based on fitness function. By this it approximately chooses only 50% of the original population to the next generation, which helps in faster convergence of the optimal solution.

One point crossover operator:

The crossover operation [5] involves the process of combining two individuals to create two new individuals. The last coinciding point in the parents is selected and the point after the coincidence is swapped, thus producing two new off springs.

(0,0)	(1,1)	(2,2)	(3,3)

Mutation:

This operator randomly chooses two points and interchanges them. After interchanging if the target position can be reached then the path is moved to next generation else the path is eliminated

Path planner algorithm:

Initialization:

1. Initialize the work space (eg.200 X 200)
2. Convert into grids
3. Using random search algorithms generate all possible paths.

Algorithm:

```
While (gen_no<max_gen_no) do
Apply fitness function
        Truncation selection
 While((next_gen_size<max_popn_size)
     Randomly choose two paths from current
     generation
          if(no_of_ iterations< crossover_rate) then
if (common cells) then
Do the crossover
Move the resulting paths to the
next_gen
          else
Choose two parents
end if
     else
     Move the parents to the next generation
     end if
         if(no_of_iterations < mutation_rate) then
     Interchange the cells in the path
if (resulting path feasible)
 Move to next generation;
else
Perform elimination;
```

The shortest possible path required for the robot to traverse is obtained.

```
for (each co-ordinate position)
if (dynamic obstacle generation = activate)
      Enter y;
      Enter the desired co-ordinate position;
else
      Enter n;
```

(0,0)	(0,1)	(1,1)	(1,2)	(2,2)	(3,3)

METHODOLOGY EMPLOYED

The size of the workspace is determined using the coordinate value (i, j). However, the size can be modified as per the requirement considerations. The maximum number of generations is an estimated random value. The workspace with the initial population will be considered as the first generation and it will iterate until the maximum number of generations is reached.

One of the important factors used in the algorithm is the Fitness function or Cost function. The method used to obtain this value is also described. The main purpose of Fitness function is to help in the selection of the desired paths that will be needed further. The variable F is used to store the value of the Fitness function. The path lengths that have value less than F will be selected. The function that is used to generate the random numbers is applied to all the above selected paths. These random values lie in the range 0 to1. These paths constitute the current generation or the first generation. The crossover rate that is defined above is employed for the random selection of two paths from the current generation.

The pair of paths selected is checked to figure out if they have any cells in common. If this condition is evaluated to be true [3], the crossover operation comes into existence. The methodology used in the operation is described above. The ultimate aim of performing these operations is to arrive at a collision free path and the application of these operators helps us do the needful. The environments in which obstacles are generated dynamically are also tested using this algorithm. Obstacles are generated as prompted as we traverse the paths [6]. In the case of generating obstacles, the co-ordinate position that is to be blocked is prompted and obtained. Re-routing of the path is done in order to reach the destination hence-forth. When the traversal path is unperturbed by the blocking co-ordinate, any sort of re-routing is considered unnecessary. The same process, as performed earlier, is iterated to find the results. The complexity of the algorithm is seen to increase exponentially as the number of obstacles in the environment augment. The desired method to traverse along any number of obstacles is tested and is experimented.

Results:

The methodology results in obtaining a shortest collision free path in the environment that is divided into a number of grids. The efficiency is tested by varying the number of obstacles in the static and dynamic environment by using different methods. For a search space of 10X10, different obstacle sizes are taken into consideration. For minimum obstacle environment, the search space is restricted to four neighbour grids that are Upper, right, left, bottom. In a moderate obstacle environment the robot moves diagonally replacing the bottom movement, in addition to the upper, right and left movements. The search space is increased to five neighbour grids (upper, right, left, upper right, upper left) in the case of complex environment. Apart from this, in the event of generating dynamic obstacles, the robot still traverses to the destination efficiently.

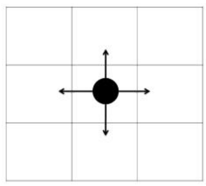

Figure 4.a Directions in which the robot moves in minimum obstacle environment

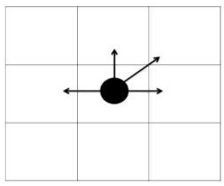

Figure 4.b. Directions in which the robot moves in moderate obstacle environment

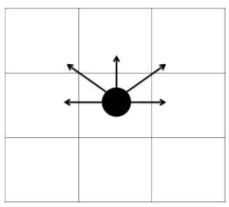

Figure 4.c. Directions in which the robot moves in complex obstacle environment.

Observations:

The variations in the number of obstacle engender the increase in the search space. The result is the reduction in computation cost and computation time that sums up to the efficacy of the algorithm

Minimum obstacle environment

Space	Obstacle size	Optimal length	Generation	Least No of optimal paths
4 (no diagonal)	28	19	10	3
4(no diagonal)	28	19	20	1
4(diagonal)	28	13	10	3

Moderate obstacle environment

Space	Obstacle size	Optimal length	Generation	Least No of optimal paths
4(no diagonal)	40	No path possible	-	-
4(diagonal)	40	13	10	1

Complex obstacle environment

Space	Obstacle size	Optimal length	Generation	Least No of optimal paths
4 (no diagonal)	50	No path possible	-	-
4(diagonal)	50	No path possible	-	-
5(diagonal)	50	13	10	1

Conclusions:

In this paper, we presented an idea using Genetic algorithm in robot motion planning for both static and dynamic environments. The fitness function used here helped in better convergence of optimal path and as complexity increased the search space of the robot was increased which proved to be better than considering all the eight neighbouring grids. Thus, the results obtained are proved to be promising.

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