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Avoiding static and dynamic obstacles and various other challenges in path planning process of robot navigation

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ABSTRACT

Purpose of the research: The most difficult aspect of robot navigation issues is considered path planning. Scientists have been studying this field for years. This domain is undergoing massive transformations. For effective path planning, a variety of approaches are used. As a result, establishing a secure robotic path in a populated environment is a critical need for most robot project's achievements.

Recent Findings: Numerous updates and novel artificial intelligence algorithms are being abused, and they are now available to the public.

Summary: This method is developed primarily to increase the quality and efficacy of globalized path planning for an autonomous mobile robot in an environment depending on the grid with the avoidance of uncertain static obstacle characteristics. The behavior of an autonomous robot can be influenced by the global path quality with respect to path consistency, smoothness, and security. The effectiveness of the Ant Colony Optimization (ACO) method has been enhanced in this work the multi-direction support.

Result: Curvature, longitudinal, and lateral coordinate restrictions are all included in the overall cost. Furthermore, for collision identification, the collection of optimum local trajectories is examined for every unpredictable obstacle at each step movement. Simulations are being used to contrast the findings to prior globalized path planning algorithms in order to distinguish the quality and efficacy of the developed technique in diverse constraint settings.

Keywords: Ant Colony Optimization (ACO), motion planning, obstacle avoidance, Challenges in path planning.

1. INTRODUCTION

Owing to its numerous applications in a variety of fields, the notion of autonomous mobility is well in recent years [1]. As a result, much investigation has been conducted to increase mobile robot autonomy. Mobile robots are used in a variety of fields, including industrial, military, and transportation sectors [2].

Autonomous robots have been employed in sectors for logistics storage, flexible production, and smart inspections. They are highly efficient than people and also accessible at a cheaper cost. Decision, perception, and action have been used to provide mobile robots with autonomous behavior autonomous [3]. Sensor-based informational data obtained from the environment are triggered to lower-level control based on judgment abilities in perception. The decision stage is familiarly known as the motion planning level. Numerous techniques are proposed to increase the capacity of mobile robots to coordinate their movements. In the intermediate phase among the actuation and perception phase, motion planning is accountable for the autonomous behavior of the robot. As per issue estimates, motion planning is generally divided into two categories namely globalized path planning (GPP) as well as localized path planning (LPP).

GPP is a fundamental approach for robots to find the best path from their starting point to their end goal. To find an ideal global path, some alternative techniques have been proposed. The majority of GPP approaches are dependent on discrete search optimization, which has been implemented in a grid-based framework. The path generated by the map grid is made up of sub-optimal locations linked by straight-line segments as well as includes abrupt bending. The global path containing the bends can create jerky movement in robots, as sudden changes in velocity as well as acceleration have an impact on the energy utilization of robots. A smoother path, on the other hand, will provide a mobile robot with a pleasant and secure ride. As a result, the curvilinear global path is already identified as a viable option for improved navigation in contemporaneous settings. In the Defense Advanced Research Projects Agency (DARPA) automated competition (2012), for instance, a vehicle followed a pre-determined curved path [4]. Because of its restricted functionality, globalized path planning techniques such as the potential functional theory [5] as well as simulated annealing algorithmic approach [6] are termed classic methods.

Han-ye Zhang [7] investigated a variety of approaches, including search algorithms depending on the graph (Visibility Graph, Tangent, and Voronoi Graphs) [8-11], Cell Decomposition method [12], Free Space method [13], Topological approach [14], Probabilistic Roadmap approach [15], Path search algorithmic approach (Dijkstra, D*, and A* algorithmic approach) [16-23], Artificial Intelligence Algorithmic approach (such as GA, ANN, PSO, ACO, SA) [24-26]. The length, duration, and weight of the path have been the primary parameters for path planning. The hit point, as well as the leaving point, is utilized along a route to build a basic Bug algorithm, often known as a common-sense algorithm [27]. Surprisingly, this algorithm is confronted with several difficulties. Bug1 algorithm [28] is later created based on bug algorithm having addressed confronted problems. ACO is the most widely used evolutionary technique for solving optimization issues. This is frequently employed to offer optimum solutions to globalized path planning challenges because of benefits including strong feedback data, resilience, better-distributed computation [29], and the flexibility to be readily integrated with different path-planning techniques.

2. CONTRIBUTION

The inspiration stems from research published in the state-of-the-art research that aims to propose a combined strategy for improving an autonomous robot's path planning skills in a knowing and unknowing statics constraint environment.

1. In the localized path planning algorithmic approach, the overall trajectory is determined by pre-defined directional points. This method provides both globalized and localized trajectory planning capabilities. An enhanced ACO version is given for global route planning which delivers an optimum trajectory with economical computing capabilities.
2. The ACO is being improved with the addition of multi-directional algorithmic approaches. Pheromone concentration is low at the first ACO iterations, thus ants must travel randomly to attain a goal point. Its computational cost is high and also time-consuming as a result of this. As a result, the computing performance of the ant colony method must be improved.
3. As a result, the Multi-directional method is used to arrange the regional nodes with an increased chance of getting an ideal global path. This improves ACO's ability to effectively supply global paths in complicated mappings. Employing the MPD trajectory performance measure, the routing reliability significantly increased. ACO generates a series of optimum grids, all of which are denoted using its center point, and then the global route is made up of straight-line segments with acute bends generated sequentially by linking grid points.

3. LITERATURE REVIEW

In modern times, great scientific attempts have been performed both in globalized and localized route planning approaches to improve the path planning efficacy of autonomous mobile robots. Due to its high benefits, ACO adopted globalized route planning in this research. ACO, on the other hand, seems to have the disadvantages of pheromone updating and delayed convergence. Several techniques are being offered to overcome this issue [30]. To increase the converging rate, the rate of pheromone has been adjusted during an effective iteration of the ACO algorithm [31]. The rate of convergence with searchability is improved by updating the pheromone updating expression and adaptively changing the volatilization rate, according to [32]. An early route is already developed and translated into preliminary pheromone dispersion in ACO algorithmic approach to prevent blind searching. In order to improve the capability of obstacle identification, a geometric technique is presented to maximize the global path followed by local dispersion of pheromones are derived from a force component specified in an artificial potential field [33]. Fuzzy logic is used with ACO to decrease repeated learning mistakes in [34]. Heuristic features enhanced ACO optimization efficiency in diverse complexity mappings, according to [35]. Linear interpolation is used in the discrete-search method for smoothing the global route [36].

The MDP model was utilized to produce a smooth route and enhance navigation [37]. Such methods may help ACO become more efficient. Moreover, because of its hardness as well as abrupt bends, then the path quality acquired in the environmental grid does not meet the dynamic characteristics of an autonomous mobile robot. A curved road is created with interpolated cubic spline in the localized route searching, and a collection of viable trajectories are constructed along the roadside to ignore static obstructions. A predictive method is utilized to ignore static as well as moving impediments while creating a curved road from preset directional points [38]. To provide optimum controlling of motion, longitudinal as well as lateral motions are incorporated inside the steering relative coordinates [39]. Utilizing localization methods dependent on LIDAR, the global route reference is generated from the vision mapping utilizing lane-level precise localization data [40]. To generate a smoother globalized path from a digital mapping employed conjugation of non-linear optimization gradient and a cubic spline curves, as well as a curvilinear coordinate's structure to acquire optimum trajectories [41]. Similarly, such approaches are good at solving localized path problems but not so good at finding the best-globalized path in a complicated constraint environment.

4. RT SHORTEST PATH PLANNING ALGORITHM:

This method was designed to discover the shortest path and avoiding obstacles of various forms. This mobile robot analyzes the whole area along the boundary for viable routes to the target point. Assuming, S as the starting location and G as the goal point. The weight of the path is indicated by Wp. Sd represents the shortest route or optimal path from the beginning location to the destination position, where d represents the distance of distance.

$$Sd \leq l + 1/2 \sum_{i=1}^{N} Oi \tag{1}$$

To determine the shortest distance of the specified terrain, the preceding formula is changed.

$$W_r = \frac{W}{UiWoi} W_{oi} \tag{2}$$

Resolve the upper bound working space to the lower bound free space using the W_r formula. This is referred to as a necessary workspace.

4.1 PROBLEM OF THIS ALGORITHM:

This algorithm's fundamental challenge is to determine the shortest path in specified terrain while eliminating rotational and transformation barriers. The primary important goals of this issue need to avoid obstacles as well as to use this method to determine a path from the beginning aim to the finishing location. In MATLAB, an autonomous mobile robot environmental code model is created. The Euclidean distance among two points has been utilized to calculate the distance among coordinating points.

$$distance = \sqrt{(x1 + y1)^2 + (x2 + y2)^2} \tag{3}$$

4.2. ANT COLONY OPTIMIZATION ALGORITHM

4.2.1. Acquiring Directional Information with Heuristic method:

In a conventional ACO, the preceding node's probability is determined using the roulette wheel technique is given below:

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\left(\tau_{ij}(t)\right)^{\alpha} \cdot \left(\eta_{ij}(t)\right)^{\beta}}{\sum_{s \in allow_k} \left(\tau_{ij}(t)\right)^{\alpha} \cdot \left(\eta_{ij}(t)\right)^{\beta}} & s \in allow_k \\ 0 & s \notin allow_k \end{cases} \tag{4}$$

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad (5)$$

$$d_{ij} = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2} \quad (6)$$

Here, τ_{ij} represents the grid path i towards grid j's pheromones, and η_{ij} is denoted as the heuristic information from i grid path towards j grid. α is denoted as the pheromone concentration-stimulating factor that determines the pheromone route's proportional effect. β is the visibility-stimulating factor that determines the heuristic information's proportional effect. The distance among nodes i and j is represented as d_{ij}. The coordinates of i grids are (x_i, y_i) and then j grid coordinates is $\left(x_j, y_j\right)$. $allow_k$ is a grid sets that ants may pick from while they're in grid i (otherwise, they're all the grids excluding the taboo grids as well as an obstacle).

4.2.2. Coverage and Updating method:

The preceding node is determined via the roulette wheel technique in the classic ACO algorithmic approach, and the process is continued till the goal point is reached. Pheromone tests are modified in accordance with path planning's length once each iteration is done. Since it allows ants to ignore all sub standardized pheromone tests and enhance their coverage efficacy to discover a shorter path, those inadequate pheromones vaporize during pheromone updating for each test, and the highest quality pheromones are upgraded to tests historical record. At the completion of every cyclic formula is utilized to increase each vertex's pheromone quantity:

$$\begin{cases} \tau_{ij} = (1-\rho)\tau_{ij} + \Delta\tau_{ij} \\ \Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \quad 0 < \rho < 1 \end{cases} \quad (7)$$

Here, m represents the number of ants, ρ is the representation of the evaporation rate of pheromones. The pheromone value which the k ant leaves in the journey of grid i towards grid j is represented by $\Delta\tau_{ij}^{k}$. The ant-cycle-system paradigm is used in this paper, and $\Delta\tau_{ij}^{k}$ is stated below:

$$\Delta\tau_{ij}^{k}(k) = \begin{cases} Q_1/L_k(t) & if\ arc(i,j) is\ used\ by\ k\ in\ iteration\ t \\ 0 & otherwise \end{cases} \quad (8)$$

Q_1 is a constant in this equation. The path length in which the ant k is seeking for is represented as $L_k(t)$.

4.3. IMPROVED ACO ALGORITHM

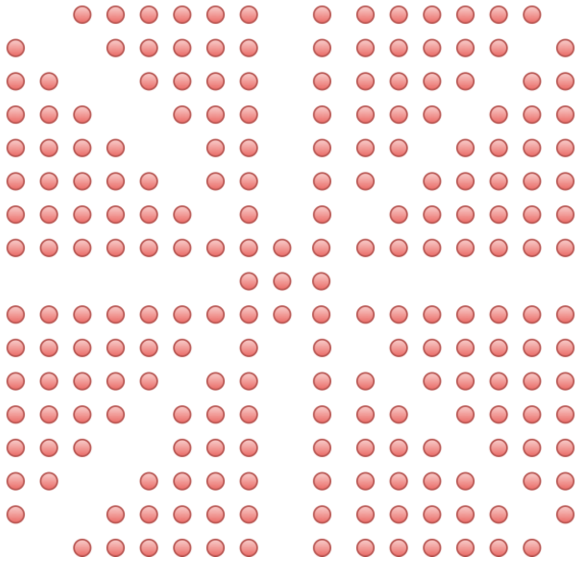

Figure 1: Visiting nodes around the center node.

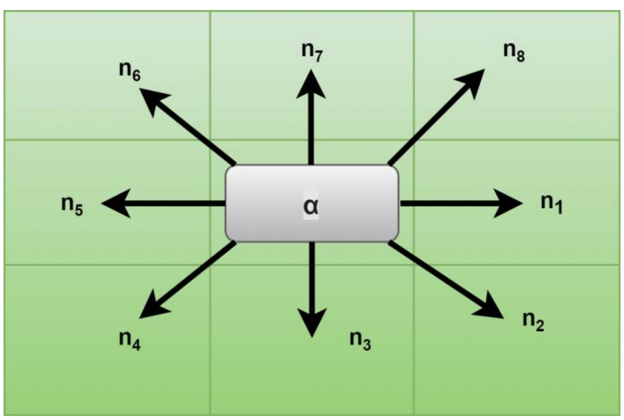

Figure 2: Visiting ant direction.

In ACO algorithmic approach, ants begin their searching in the map, and then after acquiring succeeding iteration; a fresh pheromone in this network reflects a particular route approaching a goal. Following several repetitions, the ant's trajectories begin to converge in response to a greater pheromone concentration. The ants may not possess adequate guidance via the pheromone concentration in the early generations. Thus, all move in diverse paths in pursuit of a destination node and whether the map's searching area is big and complicated, it takes longer. To aid the ACO, a new ACO algorithmic approach with multi-direction pathway searching characteristics is created. The potential linking nodes along with the node center are depicted in Figure 1. Every node's overall cost value (n) is nothing but the addition of g (n) as well as h (n), must be determined.

The Openlist, as well as Closedlist matrices, are used to list, then to identify visiting nodes. To minimize recurrence, the Openlist is tagged using visited nodes, while the Closedlist includes a database of barriers and priorly picked nodes. The preceding node is chosen depending on the f(n) of value with the lower cost. This will attempt to look for the target node till it finds it. The position of every parent node has been recorded in X Parent and Y Parent to obtain the optimal nodes. This method generates many goals across the shortest distances between the starting point and the final target. In the meantime, the optimum nodes chosen by using the multi-Directional algorithmic approach are insufficient to finish a globalized path on their own. As a result, ACOs are used to bridge the gap and establish a global route.

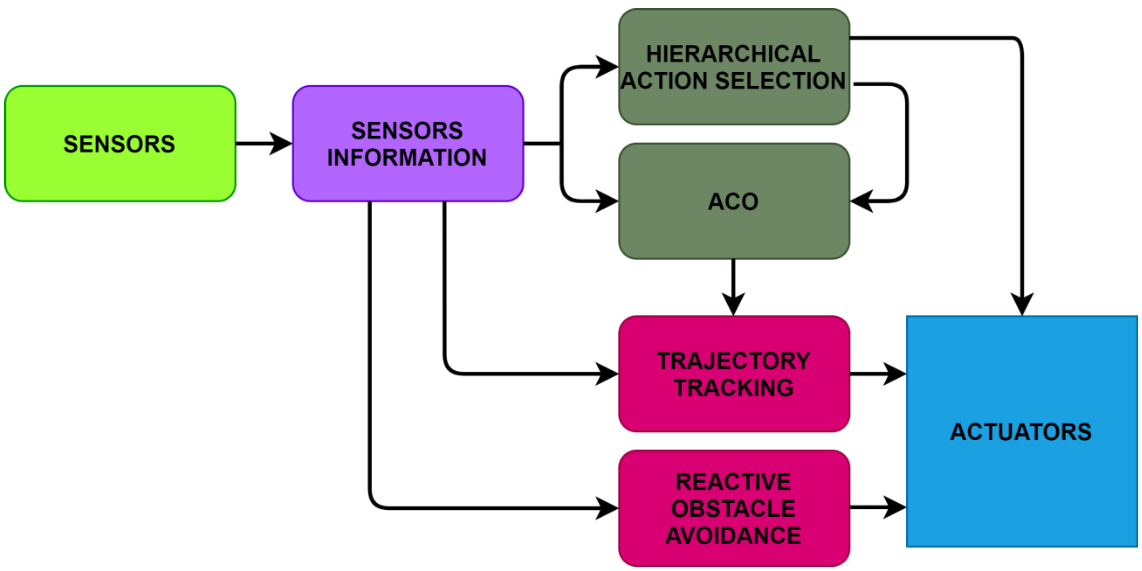

Figure 3: Control architecture for robot navigation.

In a grid-based setting, ACO was used to find the best-globalized path from a starting point to a target. ACO receives directional guidance from a multi-directional algorithmic approach. In conventional ACO, the ants must explore all potential grids, with the succeeding grid determined using the roulette wheel technique, and the process continued till the goal location is found. That took a long time to compute. In a grid-based system, the grid obstacle is denoted by 1 and then the free grid is denoted by 0. Ant may travel in eight different directions from the central grid in the lack of other restrictions, as illustrated in Figure 2. The other grid directions can be picked by employing heuristic data in the case of obstacle identification. The cost of removing a particular grid direction that does not preserve offset distances with grid obstacles is defined by the earlier restrictions policy. To increase efficacy, improved ACO heuristic features have been utilized. The ant system has been used to enhance the phenomenon update as well as premature convergence technique MAX_MIN. The basic autonomous mobile navigation with control architecture is shown in Figure 3.

4.3.1. Algorithm:

To summarize, the following are the steps involved in path planning for autonomous mobile robots using the enhanced ant colony algorithm (ACO):

Step 1: The surrounding environment is represented using the grid technique, and from the initial point the robot starts moving towards the goal point are specified.

Step 2: Set up the ant colony for the first time. Fix the ant counts, as well as its parameter that affects the heuristic value, the relative effect of the pheromone path, and few other relevant factors.

Step 3: The table of taboos should be updated. Append the present node to the relevant taboo table by placing the ant in it.

Step 4: There is a stalemate in the procedure. This will determine if ants are stuck in a stalemate situation based on the taboo table. When the ants become stuck in a deadlock, then the retraction method is used where the deadlock node has been added to the taboo table. This will determine if the ants have reached the goal place. Step 6 would be activated when the ants meet the targeted point; else, Step 5 will be activated.

Step 5: Choose the following grid. This will determine the functional probability as well as the heuristic function. Lastly, this will choose the subsequent viable grid using the roulette technique. Step 6 will be activated whether the ants approach the targeted grid; else, Step 3 will be activated.

Step 6: Whether the ants achieve the targeted node, Step 3 will be repeated still every ant has completed searching its target throughout its iteration phase, after which Step 7 will be performed.

Step 7: Pheromone should be updated. This will modify the route pheromone and assess unless it matches the convergence requirements after every iteration when the number of iterations fulfills the inequality $N \leq Nmax$. This will retreat whether the convergence requirements are met. This will proceed to Step 3 when the requirement is not yet met. The iteration counts are reordered any further when the inequality $N>Nmax$ is satisfied. As soon as the last criterion is met the outcome is produced.

5. EXPERIMENTAL ANALYSIS

In a grid-based setting, ACO is used to generate a series of optimum point grids in the coordinates of (x, y). Pathway candidates are otherwise familiar known to be center locations. The globalized route generated from path candidates is made up of substandard straight lines with severe bending, resulting in the rough path illustrated in Figure 4. This path isn't viable to sustain smoother and secure driving due to the robot's non-holonomic characteristics. LI is utilized in Figure 4 to create a midway among each of the two route possibilities shown by the dotted line.

$$f(x) = y = \frac{y_1 - y_2}{x_1 - x_0}(x - x_0) + y_0$$

Table 1: State action model of MDP.

<table>
<tr><th>STATE</th><th>ACTION BENEFIT</th></tr>
<tr><td rowspan="2">$\{m \mid m \in optimum\ path\ point\ set\}$</td><td>Either removing and keeping m in path</td></tr>
<tr><td>0 implies the removal of m and 1 implies kept m</td></tr>
</table>

Table 2: Beneficial novel policy.

If the initial neighbor directional grid is m	$Midpoint(m_i - 1\&\&m_i + 1) \neq m_i$ in which the path point count is represented as i.
Annotation	The blending point notation is given as m_i.
Benefits	Assigning 0 or 1.

A unique cost policy has been created to assess grid points to get effective computing outcomes. The primary goal of this assessment mechanism is to eliminate path points that do not comply with the costing policy. The costing policy consists mostly of the following stages: 1. The Mid-Point Assessment technique is developed to determine the direction of every point in a series. m_i represents the assessment path point, whereas $m_i - 1$ represents the first neighbors and $m_i + 1$ represents second neighbors. The path points produced by ACO are shown in Figure 5, which illustrate the sharp edges. Every grid point would be evaluated at its halfway to determine its orientation to neighbors, according to the costing policy. 2. The points of the path are evaluated using the MDP modeling approach shown in Table 1. When the two neighbor's midpoint value is identical to the centralized point, as stated in costing policy Table 2, this point would be removed from the path. As shown in Figure 6, point m does not meet the costing policy is assigned a 0 value, thus it is removed from the directional path.

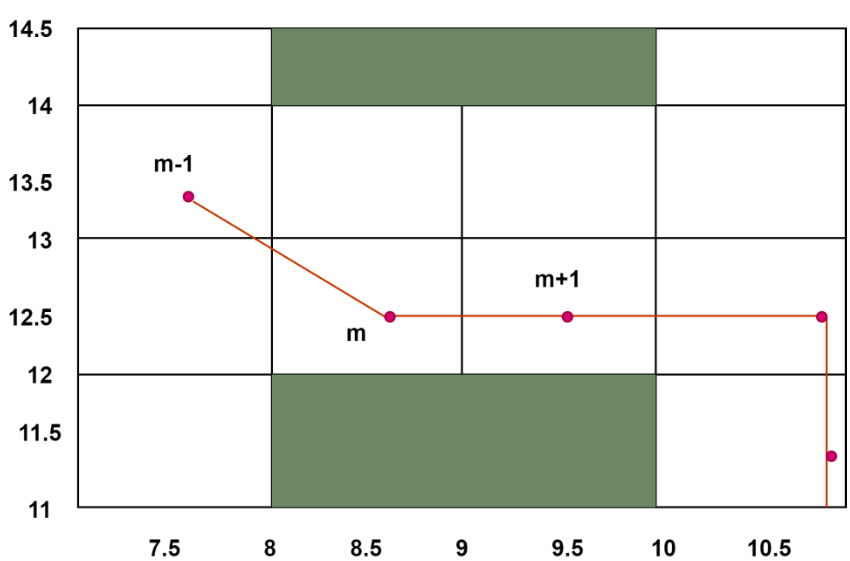

Figure 4: MDP model in between two points.

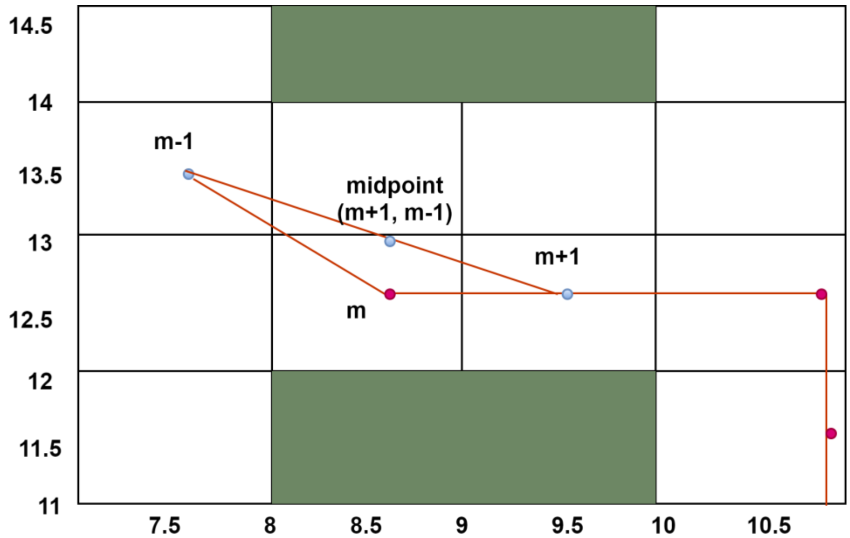

Figure 5: Determination of midpoint using costing policy.

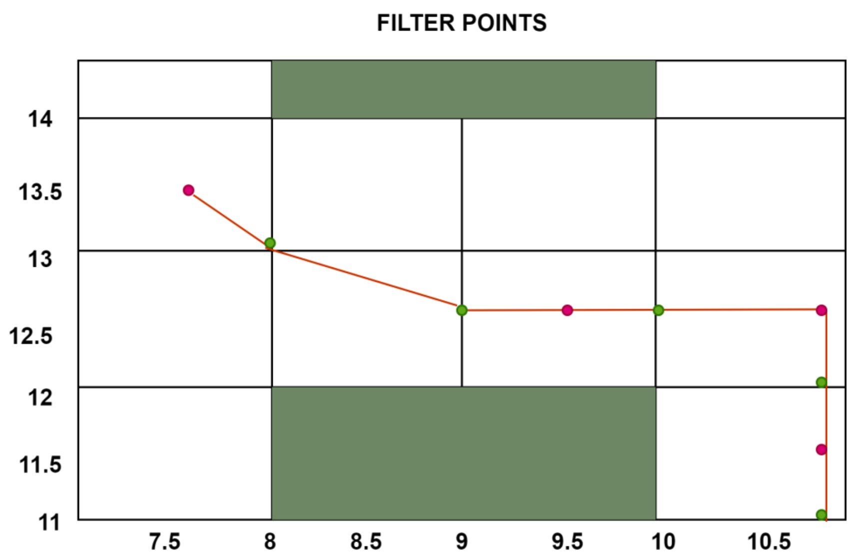

Figure 6: Removal of bad points from the navigation path.

6. CONCLUSION

This study presents a combined strategy for an autonomous mobile robot to handle and plan path issues in dynamic as well as static restrictions environments, which are tested on an autonomous robot in the real world. The reference global route is collected in the first section using a multi-directional method and an enhanced ACO algorithmic approach. To assess the globalized path points created in an environment-dependent on the grid, an MDP model depending on the beneficial scheme is proposed. Using arc-length parameterization, a globalized curvilinear route is generated from the collected waypoints. To cope with dynamic limitations in the environment, a lateral, as well as longitudinal coordinates set, is created to manage an appropriate distance offset from a globalized reference path and to construct a series of trajectories along the global pathway. A costing policy is also given for selecting the constraints-free smoother trajectory. In such a way, an ideal strategy to improving the effectiveness of diverse mappings is created in comparison to previous grid-based systems in a challenging environment, taking into account security, trajectories smoothness, and consistency path.

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