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Global and Local Path Planning for Self-Driving Car

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Abstract

An autonomous or robotic car is commonly known as a self-driving car. This vehicle can sense its surroundings, navigate, and meet human transportation needs without any human intervention, which is a significant step forward in the advancement of future technologies. Self-driving cars use GPS, cameras, lidar, radar, and navigational paths to perceive their environment. The benefits of autonomous cars, such as increased reliability, fewer traffic collisions, increased roadway capacity, reduced traffic police, reduced traffic congestion, and care insurance, are compelling for the development of autonomous vehicles. However, issues such as software reliability, cybersecurity, liability for damage, and loss of driver-related jobs must be overcome. This study aimed to investigate local and global path planning for self-driving cars using two algorithms, namely A* and the potential field algorithm. The objective was to determine the effectiveness of each algorithm and explore how they could be combined to achieve optimal results. This article proposes a path-planning approach for a self-driving car in an environment with obstacles. The path planner is based on the strategy of using both global and local planners. The global planner is designed using the A* algorithm, which is used to generate an initial global path that provides an efficient way to guarantee the shortest path to the goal in an environment. The local planner is implemented using the potential field algorithm, which is used to adjust the path in real-time based on local obstacles and other dynamic factors. The intention of using a potential function is based on its safety, simplicity, and low computational cost. The proposed approach is evaluated in a simulated environment and shows promising results in providing an efficient way to guarantee the shortest path to the goal in an environment with obstacles. The combination of global and local planning techniques is expected to enhance the robustness and safety of autonomous vehicles in real-world scenarios.

Keywords: obstacle avoidance, path planning, global planner, local planner, A* algorithm, potential function algorithm

1. Introduction

An automobile accident can happen for a variety of reasons. Driver carelessness, poor road conditions, and bad weather are occasionally caused by a mix of multiple distinct circumstances. Moreover, in our era of huge technological advancements, technologies like cars are becoming increasingly accessible to the point where almost every family owns at least one car. Thus, increasing the number of accidents exponentially.

Therefore, a gap in the market was created for self-driving cars, and self-driving Cars have gone from "maybe possible" to "definitely possible" to "inevitable." An autonomous vehicle can sense the environment, understand the surrounding scene, and make decisions without human interaction from the road to the destination [1]. The Society of Automotive Engineers has created a levels of driving automation that defines the six levels of driving automation [2], as shown in Figure 1

Level 0	**Level 1**	**Level 2**
No Automation manual control. The driver performs all driving tasks.	Driver Assistance The driver performs the driving task with some driving assist features.	Partial Autonomy The vehicle can perform functions like steering and acceleration. The driver still monitors all tasks and can take control at any time**.**
Level 3	**Level 4**	**Level 5**
Conditional Autonomy The vehicle performs the majority of the driving activities, but the driver must be ready to take control of the car at any time with notifications.	High Autonomy Under specific situations, the vehicle performs all driving functions. Although driver intervention is not required, the driver's attention is still essential.	Full Autonomy Under all conditions, the car performs all driving functions. It is not necessary for the driver to intervene or pay attention.

Figure 1 Levels of autonomous vehicles.

There are still many challenges in achieving a fully self-driving car for the masses. As they are widely known, the essential technologies of autonomous driving include environmental perception, path planning, decision making, motion control, human vehicle interface, vehicle networking, and so on [2].

In recent years, numerous path-planning approaches have been proposed to address this challenge, with various algorithms and techniques used for global and local planning. The global planning algorithms focus on finding the optimal path from the start to the destination. In contrast, the local planning algorithms handle short-term adjustments to the path in response to the environment. Recently, several studies have proposed innovative approaches to address path planning for autonomous vehicles. For example, X Zhong et al. et al. propose a hybrid algorithm that combines the A* algorithm and the adaptive window approach to handle dynamic environments with moving obstacles [3]. Similarly, W Othman et al. provides an overview of existing approaches and challenges related to using deep reinforcement learning for path planning by cooperative robots [4]. Additionally, D Kumar et al. propose a path-planning approach that uses fuzzy logic to generate smooth and flexible paths for the robot to follow in dynamic environments [5].

In this article, we propose a path-planning approach that combines the A* algorithm for global planning and the potential field algorithm for local planning. The potential field algorithm simulates the behavior of physical particles in a field of forces, with attractive forces toward the goal and repulsive forces away from obstacles. This algorithm has been shown to be effective in local planning for autonomous vehicles, as it can quickly adjust the trajectory based on changes in the environment [6]. Our proposed approach aims to take advantage of the strengths of both the A* and potential field algorithms to generate a safe and efficient trajectory for autonomous vehicles. The global planner generates an initial path that guarantees the shortest path to the destination, while the local planner adjusts the path in real time based on the current environment. Our approach is evaluated in a simulated environment, and the results show promising efficiency in generating safe paths.

2. Path planning

Path planning is an essential aspect of vehicle detection. It is defined as the process of establishing a geometric path from the vehicle's current position to a destination point while avoiding obstacles. To be considered an acceptable path, it must be feasible for the vehicle to cross and be optimal in at least one variable. For certain distance conditions, the shortest, smoothest, or fastest path that the vehicle can follow may serve as the base path. In other words, the optimal path is determined based on these factors. Path planning is commonly done by discretising the space and using the center of each unit as a moving point. Each movement location either has a barrier to avoid or is free of impediments that can be accessed. Various discretisation processes produce different motions [7] Creating an environmental map is required for path planning. Environmental map construction involves creating an exact positional description of various items in the area where the robot is located, such as road signs, obstacles, and so on. In other words, it involves the creation of a model structure or map. The goal of creating an environmental map is to enable the robot to plan the most efficient path from the starting point to the destination point within the model of the specific environment with obstacles. Path planning methods can be classified into two strategies based on the level of environmental knowledge: path planning based on global map data and path planning based on local map data [8].

2.1 Global path planning

To compute an initial path, a global path planner requires the beginning and ending points of a constructed map, which is also known as a static map. The search is performed on the constructed global map model using a global map description of the area where the robot is placed. The best algorithm will find the best path. As a result, global route planning consists of two parts: creating an environmental model and the path planning strategy [9]. Heuristic A* searching algorithm is commonly used for global path planning [10].

2.1.1 A* algorithm

In 1968, Hart proposed the A* heuristic technique. It is a common graph path planning algorithm. A* is mostly utilised to provide a nearly perfect solution with the current dataset/nodes. This approach is widely utilised in stationary environments and, in certain circumstances, in dynamic environments. The core functionality of a particular application or domain can be customised according to our needs. A* follows a road tree from its beginning point to its goal. At each iteration of its main loop, A* must choose which of its paths to extend. It determines this based on the path's cost and estimates the cost of expanding the path to the destination. Specifically, A* uses the formula below to choose the path that minimises n.

$$f(x) = g(x) + h(x) \qquad (1)$$

x is the next node on the path

g(x) represents the actual expense cost from node n to the beginning node h(x) represents the cost of the best path from n to the destination node

In the game industry, the A* algorithm is commonly employed. The A* method has since been utilised for robot path planning, graph theory, intelligent urban transportation, and automated control as artificial intelligence has advanced. The A* algorithm is a heuristic that uses heuristics to choose the best path. The A* algorithm must locate nodes on the map and apply appropriate heuristics for guidance, as shown in Figure 2. Table 1 contains standard heuristic functions such as Manhattan distance, Euclidean distance, and Cross distance [11], [12].

Table 1 Most Common Types of Heuristic Functions Used in Path Planning Algorithms.

Function	Equation
"Euclidean distance"	"$\sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2}$"
"Manhattan distance"	"$\lvert X_1 - X_2 \rvert + Y_1 - Y_2 \rvert$"
"Octile distance"	"Max $(\lvert X_1 - X_2 \rvert, \lvert Y_1 - Y_2 \rvert)$"

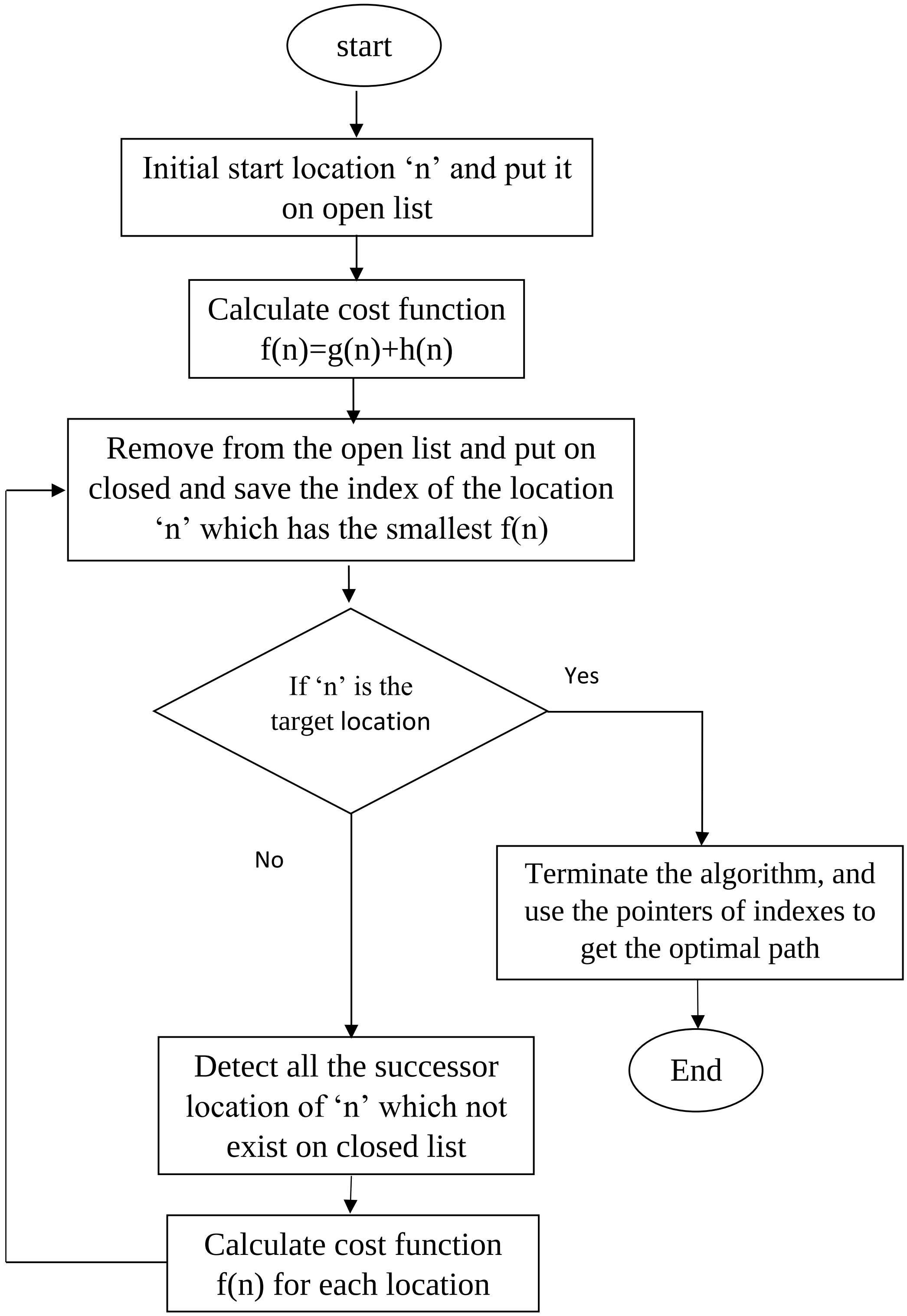

Figure 2 Path planning flowchart using the A* algorithm.

2.2 Local path planning

Path planning that requires the robot to navigate in an uncertain or dynamic environment is known as local path planning. The algorithm will adapt to barriers and changes in the environment wherever it is used for path planning. Local route planning may be characterised as real-time obstacle avoidance employing sensory-based information on contingencies impacting the robot's safe navigation. Normally, a robot is driven with one path in local path planning .The shortest path from the starting position to the goal point is a straight line, which the robot follows until it encounters an obstruction. The robot then executes obstacle avoidance by deviating from the line while also updating certain key information, such as the updated distance from the present location to the goal point, the obstacle departure point, and so on. In order to reach the destination exactly, the robot must constantly know the position of the destination point from its present position in this type of path planning. The potential field approach is a well-known local path planning technique[13].

2.2.1 Potential field method

The function's basic objective will be to predict a comprehensive path-planning algorithm that takes the robot via vector quantities of the target's attractive force and repulsive forces from obstacles in the area. The aim is to discover a direct path from the robot's starting point to the destination position while avoiding obstacles. The potential functions to be investigated are differentiable real value functions; hence, given that the potential function's value is energy, the gradient of this function will create the force. A potential field gradient is predicted to drive the robot to the goal position based on this simple but powerful assumption.

The job's success is dependent on the robot's possible attractive and repulsive gradients. The robot and the rest of the obstacles are believed to be positively charged, whereas the target is supposed to be negatively charged. This charge difference produces repulsive forces that push the robot and pull the target. The potential function is the sum of the potential attractive and repulsive of a robot.

$$\mathrm{U} = \mathrm{U_{att}} + \mathrm{U_{rep}} \qquad (2)$$

U_{att} is the attractive potential field

U_{rep} is the repulsive potential

Attraction tends to drag the robot toward the desired place, while repulsion drives the robot away from obstacles. The gradient U yields a vector field for artificial forces F(d).

$$F(d) = -\nabla U_{att} + \nabla U_{rep} \qquad (3)$$

$$F(d) = -F_{att} + F_{rep} \quad (4)$$

∇U is the gradient vector of U at robot point d (x, y)

F_{att} is an attractive force

F_{rep} is an attractive force

Kathiep's general form of suitable potential field functions is given below.

(a) attractive potential field and force

$$U_{att} = \frac{1}{2}\zeta d^2 \quad (5)$$

$$F_{att} = \nabla U_{att} = \zeta(d) \quad (6)$$

ζ is the attractive potential coefficient

$d = |\, d_{vehicle} - d_{goal}\,|$

$d_{vehicle}$ is the vehicle position at (x, y)

d_{goal} IIs the goal position at (x, y)

The attractive force is a linear function that decreases as the vehicle nears the goal.

(b) repulsion potential field and force

$$U_{rep} = \begin{cases} \frac{1}{2}\eta\left(\frac{1}{d} - \frac{1}{d_\circ}\right)^2 = \frac{1}{2}\eta(\ln d - \ln d_\circ)^2 & if\ \mathrm{d} \leq d_\circ \\ 0, & if\ d > d_\circ \end{cases} \quad (7)$$

$$F_{rep} = \nabla U_{rep} = \eta e^{-|d - d_\circ|} \quad (8)$$

η is the repulsive potential coefficient

$d = |\, d_{vehicle} - d_{obstacle}\,|$

$d_{vehicle}$ is the vehicle position at (x, y)

$d_{obstacle}$ is the obstacle position at (x, y)

$d_\circ$ is the influence of distance.

The repulsion capability ensures that the potential increases significantly as the vehicle approaches the obstacle and has no effect when the car is further away[14].

3. Simulation and Discussion:

A self-driving car simulation was utilised to plan the path for an autonomous vehicle to move from the starting point to the endpoint. The program initially selects and presents the map on which the vehicle will operate, along with the starting and target locations. Next, the A* algorithm is used for global path planning, and the Potential field algorithm is employed for local path planning. The A* algorithm generates a global path from the start to the target by executing on the known environment, aiming to avoid getting stuck in local minimums that may exist on the map in the absence of considering any obstacles. The path provided by the A* algorithm is then defined at multiple equally spaced path points, which serve as potential intermediate field targets.

The Potential field algorithm calculates the direction of the planner by determining the attractive and repulsive potentials of each potential direction. The attractive potential is based on the distance between the current location and the goal, while the repulsive potential is based on the proximity of obstacles. This means that the path point closest to the vehicle's starting position will generate an attractive starting potential field. As the vehicle approaches this coordinate, it will stop pulling and turn towards the next closest point. Intermediate waypoints guide the vehicle across the map, allowing it to navigate through obstacles in real time. The potential domain diagram is executed at each time step, generating a path up to a few time steps into the future. The primary purpose of using such potential field targets is to ensure that the vehicle can successfully navigate through the map while avoiding obstacles.

This study aimed to investigate local and global path planning for self-driving cars using two algorithms, A* and the potential field algorithm. The objective was to determine the effectiveness of each algorithm and explore how they could be combined to achieve optimal results. The findings indicated that the A* algorithm was highly effective in planning the global path, irrespective of obstacles. However, it had limitations in terms of local planning, which could lead to collisions with obstacles if not properly addressed. Figure 3 illustrates the global path planning using the A* algorithm.

On the other hand, the potential field algorithm was effective in local planning as it considered the influence of obstacles on the car's movement in real-time. However, it sometimes got into closed road problems when planning the path, limiting the car's ability to navigate the environment. Figure 4 shows an example of closed roads in the planned path using the potential field algorithm.

To address the limitations of both algorithms, a combination of A* and the potential field algorithm was used. The simulation results showed that the planner was able to navigate around obstacles and follow the road map to reach the goal. The planner used the potential field algorithm to determine the direction in which it should travel, and the A* algorithm was used to determine the best path between the planner's current location and the goal. The combination of these two algorithms ensured that the planner was able to navigate around obstacles and reach the goal efficiently. In addition, it is important to note that the time required by the proposed system for route planning may vary depending on the size of the map, the complexity of the route, and the performance of the device used for path planning. Our work was tested in a closed environment with moving obstacles for four different paths, and all results were good, confirming the effectiveness of our proposed approach. Figure 5 to Figure 8 shows the final path planned using the combined approach.

In summary, the A* algorithm and potential field algorithm proved to be an effective combination, providing a comprehensive approach to path planning that enhances the safety and efficiency of self-driving cars.

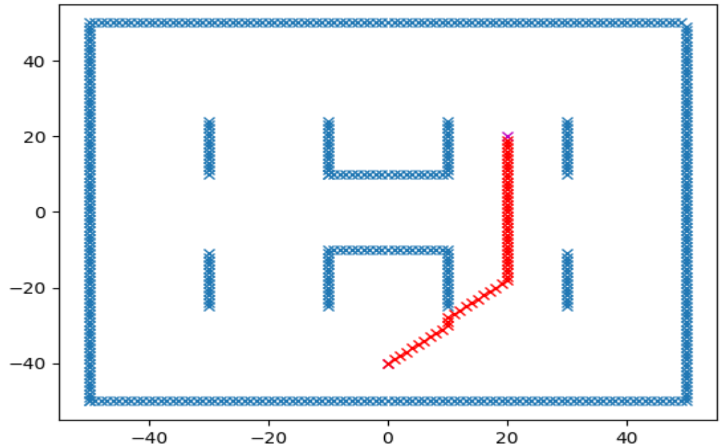

Figure 3 Global path planned using A* algorithm.

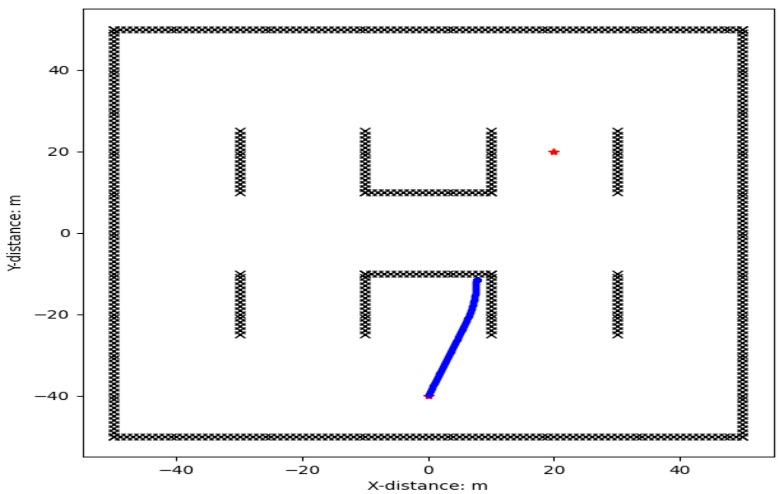

Figure 4 Example of closed roads in potential field algorithm path planning.

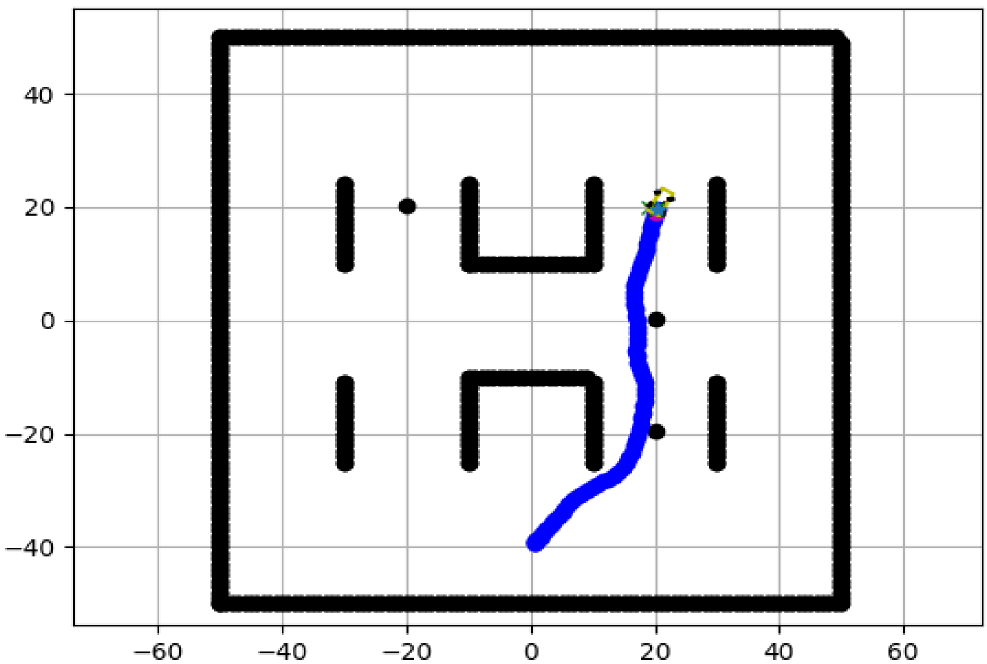

Figure 5 path planning simulation result from (0,-40) to (20,20) using combined A* and potential field algorithm.

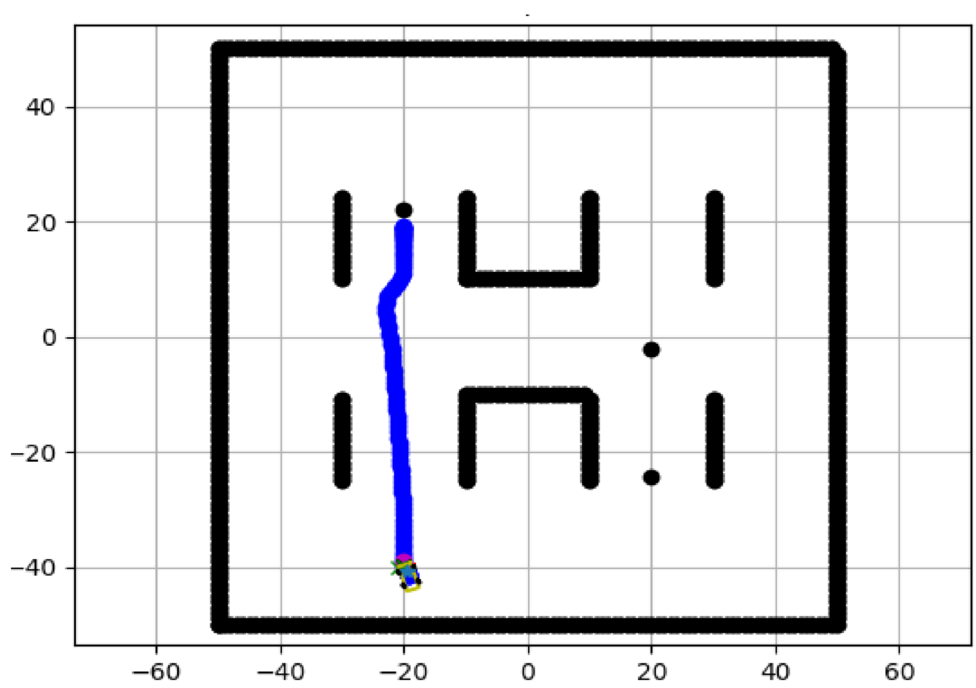

Figure 6 path planning simulation result from (-20,20) to (-20,-40) using combined A* and potential field algorithm.

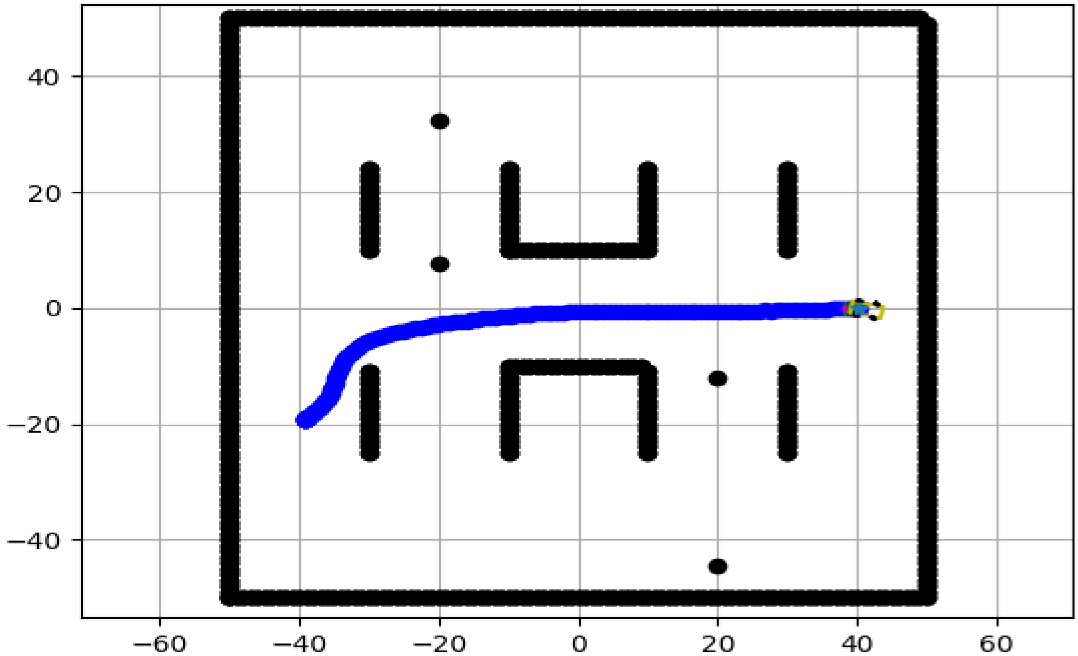

Figure 7 path planning simulation result from (-40,-20) to (40,0) using combined A* and potential field algorithm.

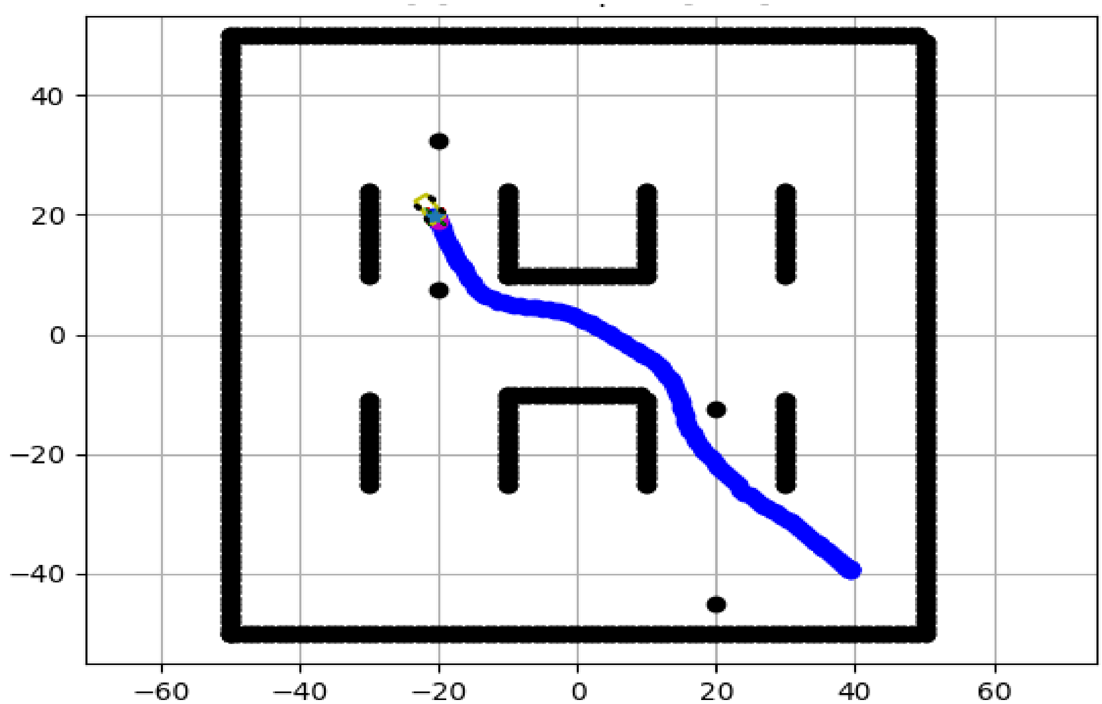

Figure 8 path planning simulation result from (40,-40) to (-20,20) using combined A* and potential field algorithm.

4. Conclusion

In conclusion, the combination of the A* algorithm for global path planning and the potential field algorithm for local path planning has proven to be a promising approach for self-driving cars. A* algorithm finds the shortest path between two points by considering the distance and cost associated with each possible path. On the other hand, the potential field algorithm creates a repulsive force around obstacles and an attractive force towards the destination, guiding the car along a safe and feasible path. This approach enables the self-driving car to plan and execute smooth and efficient trajectories, even in complex environments with obstacles and dynamic elements. Furthermore, the use of these algorithms can enhance the safety, reliability, and performance of self-driving cars, reducing the risk of accidents and improving the overall driving experience for passengers.

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تخطيط المسار العام والمحلي للسيارات ذاتية القيادة

الخلاصة: *تُعرف السيارة المستقلة أو الآلية عمومًا باسم السيارة ذاتية القيادة. هذه السيارة قادرة على استشعار البيئة والملاحة وتحقيق إمكانات النقل دون أي تدخل بشري. إنها خطوة كبيرة في تطوير تكنولوجيا المستقبل. تستشعر السيارات المستقلة محيطها بالكاميرات والرادار ونظام تحديد المواقع العالمي والمسارات الملاحية. تعتبر مزايا السيارات ذاتية القيادة، مثل تقليل الاصطدامات المرورية وزيادة الموثوقية وزيادة سعة الطرق وتقليل الازدحام المروري وكذلك تقليل شرطة المرور وتأمين الرعاية. لذا أصبح لزاما تطوير السيارات ذاتية القيادة على الرغم من أنه يتعين علينا التغلب على مشكلات الأمن السيبراني، وموثوقية البرامج، ومسؤولية الضرر وفقدان الوظائف المتعلقة بالسائق. هدفت هذه الدراسة إلى التحقيق في تخطيط المسار العام والمحلي للسيارات ذاتية القيادة باستخدام خوارزميتين، وهما A* وpotential field. كان الهدف هو تحديد فعالية كل خوارزمية واستكشاف كيفية دمجها لتحقيق أفضل النتائج. توضح هذه المقالة نهج تخطيط حركة السيارة ذاتية القيادة في بيئة فيها عقبات، حيث تم تصميم المخطط العام باستخدام خوارزمية A*، والتي تُستخدم لإنشاء مسار عام أولي يوفر طريقة فعالة لضمان أقصر مسار إلى الهدف في بيئة ما. يتم تنفيذ المخطط المحلي باستخدام خوارزمية potential field، والتي تُستخدم لضبط المسار في الوقت الفعلي بناءً على العوائق المحلية والعوامل الديناميكية الأخرى. تعتمد نية استخدام وظيفة محتملة على سلامتها وبساطتها وتكلفة حسابية منخفضة. يتم تقييم النهج المقترح في بيئة محاكاة ويظهر نتائج واعدة في توفير طريقة فعالة لضمان أقصر طريق إلى الهدف في بيئة بها عوائق. من المتوقع أن يؤدي الجمع بين تقنيات التخطيط العامة والمحلية إلى تعزيز متانة وسلامة المركبات المستقلة في سيناريوهات العالم الحقيقي.*