JTE HCMUTE
ISSN: 2615-9740

JOURNAL OF TECHNICAL EDUCATION SCIENCE
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An Optimal Smooth-Path Motion Planning Method for a Car-like Mobile Robot

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ARTICLE INFO

Received:	09/09/2022
Revised:	17/10/2022
Accepted:	04/11/2022
Published:	28/02/2023

KEYWORDS

Smooth-path motion planning;
Car-like mobile robot;
Genetic algorithm;
Potential field;
Dubins curve;
Nonholonomic constraints.

ABSTRACT

This paper proposes an optimal motion planning method consisting of a genetic algorithm (GA), potential field (PF), and Dubins curve for a Car-like mobile robot to solve the problem of finding the shortest and most feasible path in the global environment. Firstly, the GA finds the shortest path by evaluating, selecting, crossing over, and mutating from the initial population and finally provides the strongest individual evolution. Then the result from the GA is further applied with the PF algorithm to improve the ability of obstacle avoidance in the environment. Finally, the Dubins curve method is combined to smooth the path and helps the Car-like mobile robot solve the nonholonomic constraints problem. The major advantages of this method include finding the shortest path, improving avoidance obstacle ability, and smoothing the output path in an environment effectively. The simulation of the proposed method is executed on MATLAB to verify the ability to solve motion planning problems for a Car-like mobile robot.

Doi: https://doi.org/10.54644/jte.75A.2023.1276

1. Introduction

In recent years, the application of mobile robots has expanded into many fields, such as agriculture, manufacturing, military, and rescue [1]. Mobile robots are robots capable of moving from the original position to the goal one, which may have less interaction with humans or not. Mobile robots are divided into various types [2], on the ground with wheeled mobile robots (WMRs) [3], legged mobile robots (LMRs) [4], on the air with unmanned aerial vehicles (UAVs) [5], and underwater with autonomous underwater vehicles (AUVs) [6]. Among them, WMRs are prioritized due to low system complexity and strong application-level characteristics. WMRs have various models, such as the differential, tricycle, omnidirectional, and so on. Specifically, a Car-like mobile robot model is easy to control and is familiar with popular vehicles in practice, which is mentioned in this paper.

In order to navigate the Car-like mobile robot in a realistic environment, path planning is a major issue that needs to be resolved [7]. The primary purpose of mobile robot path planning is to find a path from the start to the endpoint with a collision-free condition, possibly the shortest path [8]. Generally, path planning problems can be divided into two main types: local path planning and global path planning. The local path planning algorithms are used for finding the path between the start node and the end node in an unknown environment. These algorithms are evaluated as not optimal in terms of length path and time consumption, such as PF [9], behaviour decomposition method [10], rolling windows algorithm [11], and so forth. Besides that, the global path planning algorithms have the resulting path nearly-optimal or optimal in the known environment, such as the A* algorithm [12], Rapidly Random Tree* (RRT*) [13], optimization algorithms [14], [15], so on. Due to the superior optimization, global algorithms are considered to be used in the known environment, especially the optimization algorithms. Recently, the GA has been the most interesting optimization algorithm for solving robot path planning problems in single and multiple targets, developing Matrix-Binary Codes, or producing an optimal path for autonomous mobile robots in the static environment [16]–[18]. However, GA cannot obtain the best results for autonomous navigation in practice whenever any obstacle suddenly appears.

Some hybrid methods have been proposed to overcome the above limitation of the GA. The repulsive potential field (RPF) of the PF is combined with GA to improve obstacle avoidance and minimize collision during the robot's performance. Some studies use combined methods with PF to solve path planning problems, which encounter the local minima trap of PF, while the above-combined method does not meet this situation [19], [20]. Moreover, the above studies do not concern with the nonholonomic problem. Therefore Dubins curve method is applied for smoothing to improve the operational ability of the robot.

Based on the aforementioned analysis, this paper proposes an optimal motion planning method for a Car-like mobile robot based on the combination of the GA, PF, and Dubins curve. Firstly, the GA generates the most feasible and shortest path in the global environment. After that, the obtained path from the GA is applied with the PF algorithm to enhance the obstacle avoidance ability in practice. Finally, the Dubins curve method is considered to replace sharp turns with smooth turns on the path from GA and PF to help the Car-like mobile robot model operate. The proposed method's simulation is implemented on MATLAB to evaluate the ability to resolve motion planning issues for a Car-like mobile robot.

The structure of this paper is organized as follows: The model of the Car-like robot is presented in the next section. In section 3, the combination of GA, PF, and Dubins curve are mentioned. Simulation results are presented in Section 4. Section 5 includes the conclusion and suggestions for future research.

2. Car-like mobile robot model

As the most common and convenient way of transportation, Car-like mobile robots have triggered an upward trend for research in the autonomous field. In Figure 1, the Car-like model contains four wheels devised into two parts. The first part is two rear wheels fixed parallel to the vehicle's body. The other part is two steering front wheels that also parallel together. It can turn left or right with an angle but cannot immediately move sideways, which is known as a nonholonomic system [21].

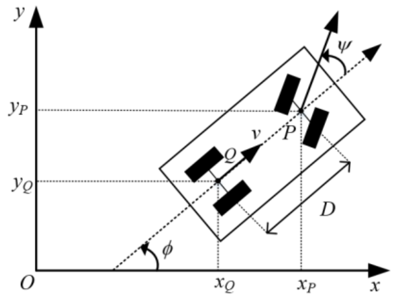

Figure 1. *Car-like mobile robot model*

where, Q is the center of gravity between the rear wheels, P is the center of gravity between the front wheels, and D is the distance between the front and rear wheels.

The state transition robot is represented by a vector:

$$\mathbf{x} = \begin{bmatrix} x_Q & y_Q & \phi \end{bmatrix}^T \tag{1}$$

where x_Q, y_Q are the coordinates of Q on the coordinate axis and ϕ is the orientation angle of the robot and the environment's global x-axis. There are two nonholonomic constraints, one for each pair of wheels, shown below [2]:

$$\begin{aligned} -\dot{x}_Q \sin\phi + \dot{y}_Q \cos\phi = 0 \\ -\dot{x}_P \sin(\phi+\psi) + \dot{y}_P \cos(\phi+\psi) = 0 \end{aligned} \tag{2}$$

where x_P, y_P are the coordinates of P on the coordinate axis and ψ is the steering angle of the front wheels when rotating. The control signal of the robot is defined as

$$\mathbf{u} = \begin{bmatrix} v & \psi \end{bmatrix}^T \tag{3}$$

where v is the velocity of the rear wheels when rolling.

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Assume that the wheel rolls without slipping, from (1) and (3), the kinematic equations for a rear-wheel driving car are described by [2]:

$$\begin{aligned} \dot{x}_Q &= v\cos\phi \\ \dot{y}_Q &= v\sin\phi \\ \dot{\phi} &= v\frac{\tan\psi}{D} \end{aligned} \tag{4}$$

Here, there is a singularity at $\psi = \pm\pi/2$, which corresponds to the "jamming" of the vehicle when the front wheels are normal to the longitudinal axis of its body. In this paper, the steering angle is limited:

$$-\pi/2 < \psi < \pi/2 \tag{5}$$

Assume the linear velocity of the robot is considered a constant $(v = const)$, and the robot can only move forward $(v > 0)$.

3. Smooth-path motion planning based on genetic algorithm, potential field and Dubins curve

In this section, a combination of GA, PF, and Dubins curve is proposed to find the shortest and most feasible path in the global environment for motion planning in mobile robots. The method is performed in 4 steps: Step 1: GA finds the feasible and shortest path; Step 2: The influence area by the RPF of the obstacle is checked; Step 3: A new path is found based on the repulsive force (RF); Step 4: Shape turns are replaced into Dubins curve to obtain the final path. An overview of the proposed method is illustrated in Figure 2.

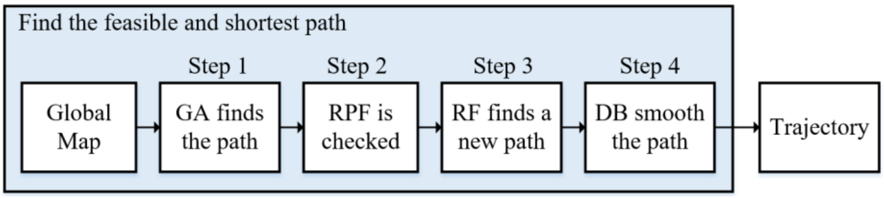

Figure 2. *Steps of the proposed method*

3.1. Find the shortest feasible path with genetic algorithm

First, GA is used to find a path from the start node to the goal node that does not intersect with obstacles. The detailed steps of GA are described below. The pseudocode of GA is shown in Figure 3.

	Genetic algorithm
1.	**Input:** N : Population size; P_c : Crossover rate; P_m : Mutation rate
2.	**Output:** Best chromosome (the shortest path)
3.	$\text{Gen} \leftarrow 1$
4.	Initialize randomly the initial population $P(\text{Gen})$
5.	Evaluate $P(\text{Gen})$ using a fitness function
6.	**While** (not termination condition) **do**
7.	Select $P(\text{Gen})$
8.	Crossover $P(\text{Gen})$
9.	Mutation $P(\text{Gen})$
10.	Evaluate $P(\text{Gen})$
11.	$\text{Gen} = \text{Gen} + 1$
12.	**End**

Figure 3. *The pseudocode of GA*

Initialization of the population – GA starts with an initial population, and each individual in the population (also called a chromosome) represents a feasible path. The algorithm begins with initializing

N random paths and adding to the population. The concrete steps are as follows: Step 1: A path is randomly created; Step 2: The path created in step 1 is checked for feasibility, if this path is feasible, add it to the population; otherwise, remove it and go back to Step 1; Step 3: The number of paths in the population is checked, if there are enough N paths, end the population initialization step, if not enough, go back to Step 1. Figure 4 illustrates feasible and infeasible paths. A population of N randomly initialized chromosomes can be represented as:

$$\text{Initial Population} = [P_1, P_2, \dots, P_N] \tag{6}$$

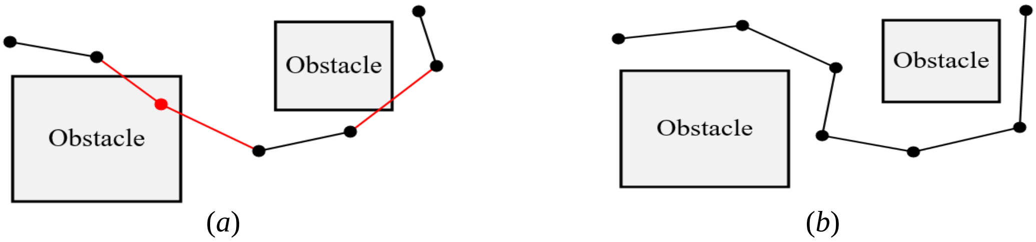

Figure 4. *(a). The infeasible path. (b). The feasible path*

Fitness function – The evaluation of individuals is through the fitness function, the individual with better fitness will survive through natural selection. The fitness function is presented as follows:

$$f(P_i) = \frac{1}{L(P_i)} \tag{7}$$

where $f(P_i)$ is the fitness of the chromosome $P_i(i = 1, \dots, N)$, $L(P_i)$ is the length of the path corresponding to that chromosome.

Selection operators – Selection is an important operator in GA, it directly determines the quality of the path. Linear ranking selection is used in the proposed method, in which individuals are sorted in order of increasing fitness, the best chromosome is ranked N, otherwise is ranked 1 [22]. The selection probability of each individual is linearly proportional to its rank:

$$p_i = \frac{1}{N}\left[\eta + 2(1-\eta)\frac{i-1}{N-1}\right] \tag{8}$$

where p_i is the selection probability of individual P_i, and η is the selection coefficient $(0 < \eta < 1)$.

Crossover operators – Crossover is a way of exchanging information among chromosomes. Two individuals, called the parent chromosome, are randomly selected to perform the crossover with the probability P_c. This algorithm proposes a one-point crossover, randomly selecting a common gene except for the start node and the goal node between two parent chromosomes to conduct the crossover, resulting in two offspring chromosomes. After performing the crossover, the offspring chromosomes are checked for feasibility. Offspring chromosomes are replaced with parent chromosomes in the population if they are feasible; otherwise, keep the parent chromosomes. Figure 5 and Figure 6 illustrate two cases of one-point crossover.

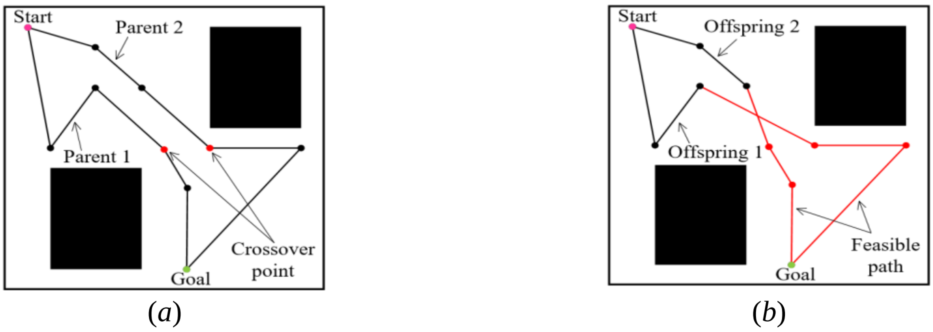

Figure 5. *The case of feasible offspring where (a) is before crossover, (b) is after crossover*

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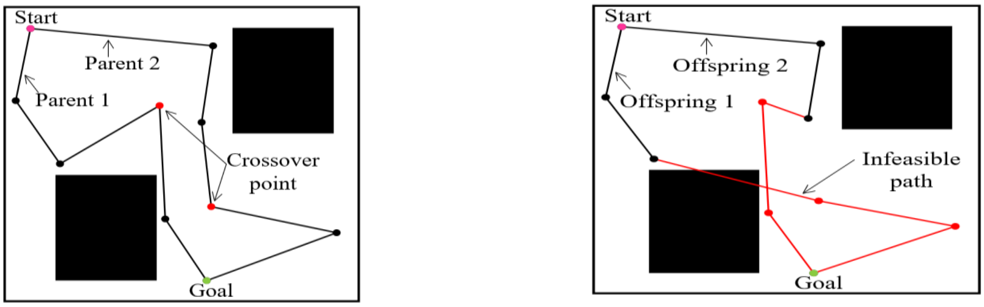
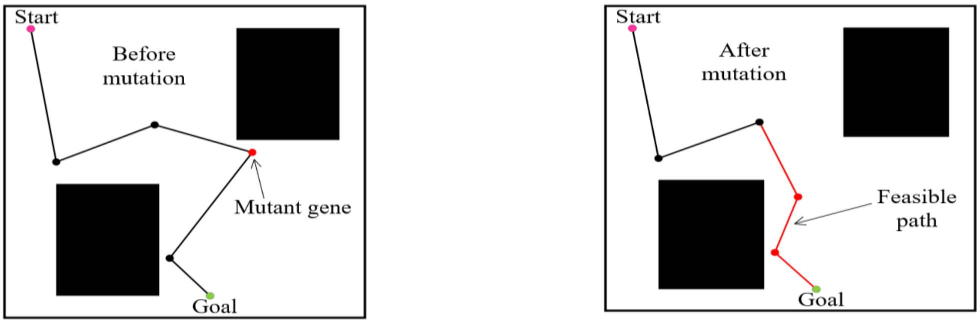


(*a*) (*b*)

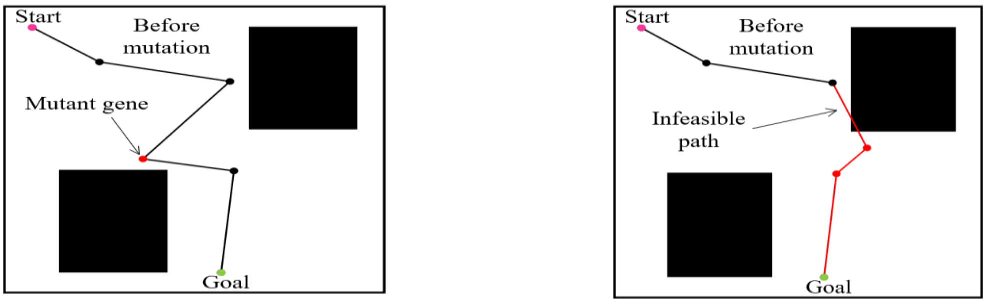
Figure 6. *The case of infeasible offspring where (a) is before crossover, (b) is after crossover*

Mutation Operators – Mutation is an operator that changes one or more genes on a chromosome into another gene. Mutation expands the search space across the environment, thus ensuring a global search, increasing population diversity, and avoiding premature convergence. However, mutation only occurs with a low probability P_m because this operator can lose individuals with high fitness, leading to inefficient GA. Figure 7 and Figure 8 illustrate two cases of one-point mutation.



(*a*) (*b*)

Figure 7. *The case of feasible offspring where (a) is before mutation, (b) is after mutation*



(*a*) (*b*)

Figure 8. *The case of infeasible offspring where (a) is before mutation, (b) is after mutation*

3.2. The effectiveness of the potential field algorithm

GA is used to find the shortest feasible path from a given initial population in the global environment. The output path of GA may be nearly optimal or optimal path based on the criteria of the fitness function. However, the distance between the path at tight corners or locations near obstacles is very narrow and may affect the actual operation. Therefore, the RPF of the PF algorithm is applied to make the path in GA more reasonable and far from obstacles. The RPF generates RF that pushes the nodes of the path away from the obstacle. The formula of RPF is described below [23]:

$$U_{rep}(q) = \begin{cases} \dfrac{1}{2}\xi\left(\dfrac{1}{D(q)} - \dfrac{1}{Q^*}\right)^2 & , D(q) \le Q^* \\ 0 & , D(q) > Q^* \end{cases} \tag{9}$$

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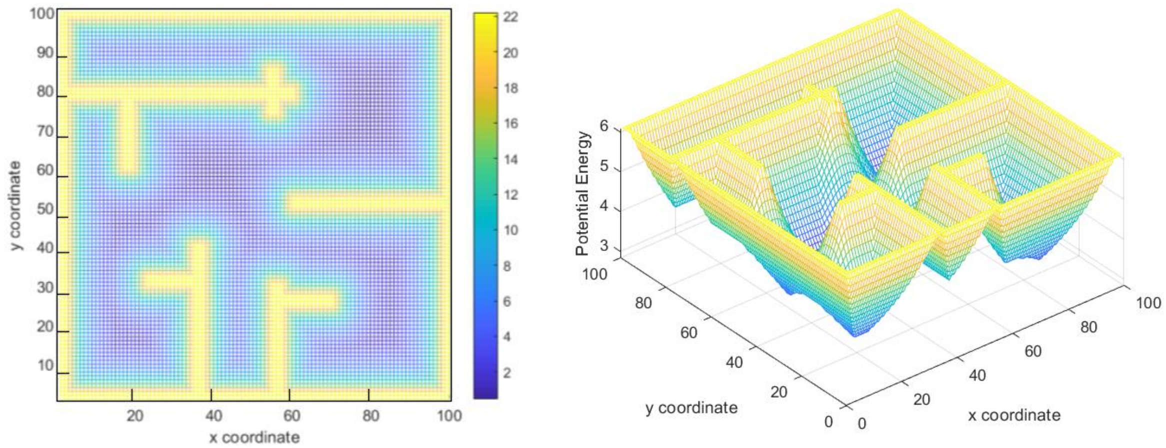
where ξ is the attractive coefficient, $D(q)$ is the distance from the obstacle to the point under consideration, and Q^* is the threshold of influence of the RPF at the obstacle. The closer our robot is to the obstacle position, the greater the thrust will be. The magnitude of the RPF acting on the map is in Figure 9.



(a) (b)

Figure 9. *The repulsive potential field in the 2D environment (a) and the 3D environment (b)*

From the above RPF functions, the RF effect on each point in the map is described:

$$F_{rep} = -\nabla U_{rep}(q) = \begin{cases} \xi\left(\dfrac{1}{Q^*} - \dfrac{1}{D(q)}\right)\dfrac{1}{D^2(q)}\nabla D(q) & , D(q) \le Q^* \\ 0 & , D(q) > Q^* \end{cases} \tag{10}$$

This force function calculates the distance from each node on the GA's output path to the obstacles surrounding it. If the distance to the obstacle is less than the threshold of the RPF, the node is subjected to the RF to help it get out of range, or if the distance is greater than the threshold, then RF is zero. The PF algorithm checks all nodes of the path from the GA, so it helps the path avoid obstacles more effectively, as shown in Figure 10.

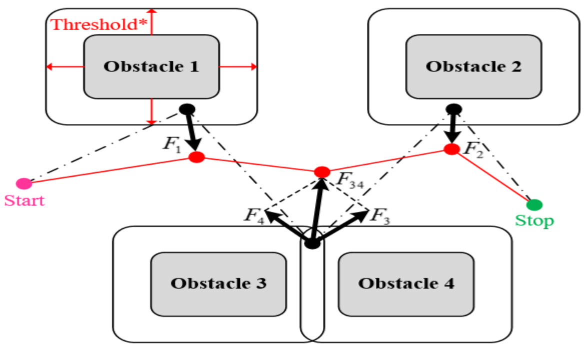


Figure 10. *The improved path with repulsive force*

3.3. Path motion planning with Dubins curve

After being improved by the RPF, a path is completely created. However, there have some problems with nonholonomic mobile robots. The Dubins curve is added to the path to deal with this problem. Dubins curve uses some basic geometry knowledge of curves and circles to create a smooth path suitable for a nonholonomic robot. To be precise, the Car-like robot needs to move at a constant speed, and the steering angle is fixed at the maximum radian [24]. The Dubins curve can be divided into L, R, and S, corresponding to turning left, right, and straight. With this combination, there are six Dubins curve categories path: LRL, RLR, LSR, RSL, LSL, and RSR, as shown in Figure 11. These kinds of path are divided into two types CSC and CCC (C stand for Curve, and S stand for Straight).

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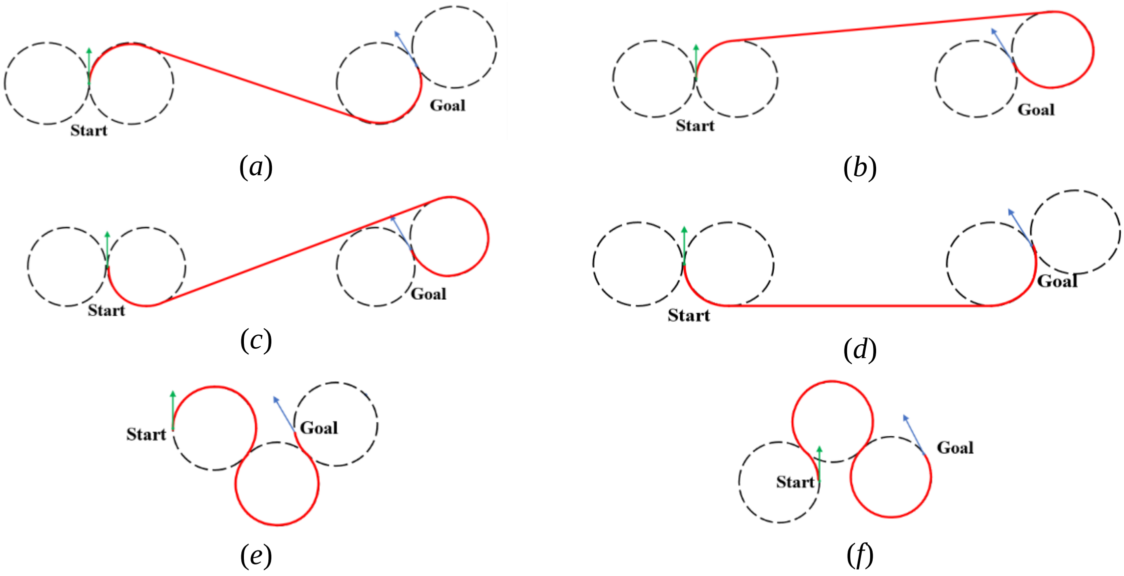

Figure 11. *Six types of Dubins curve include (a) RSL, (b) RSR, (c) LSR, (d) LSL, (e) RLR, (f) LRL*

Dubins curve is generated by two given poses; it uses the position and direction of the poses with a constant steering angle of the wheel can create a path that can be applied to smooth the path and suit the Car-like robot.

4. Simulation

This section demonstrates the proposed method's effectiveness in solving the problem of path planning and motion-smoothing for a Car-like mobile robot with two different scenarios. The first scenario is where the obstacle is far from each other and have much free space. The second scenario is run on a complex map that is less collision-free and has more obstacles. Both scenarios are tested on MATLAB R2019a software.

4.1. First scenario: simple map with fewer obstacles

In the first scenario, the 2D map is set with a size is 100x100 units. The obstacles are black rectangles, the white area is free space, and a pink and green point is regarded as the start and goal node, respectively. The map is shown in Figure 12.

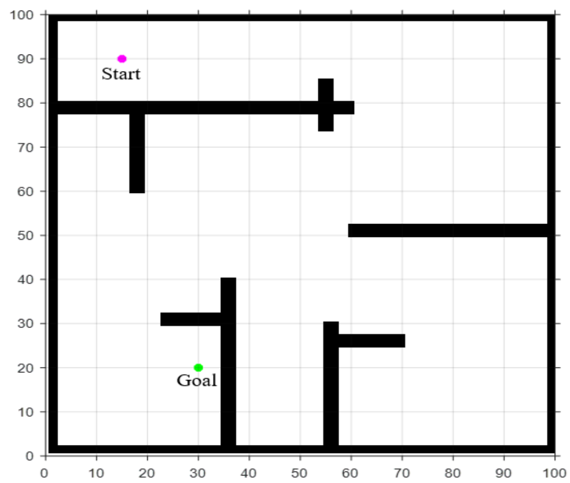

Figure 12. *The map for the first scenario*

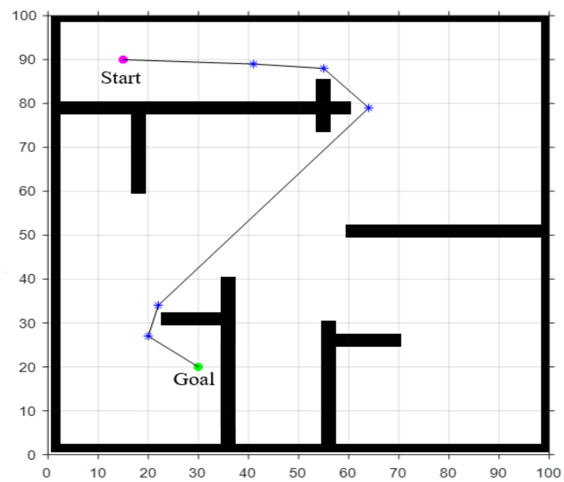

Figure 13. *GA finds the shortest feasible path in the global environment*

In this case the parameter are used is based on table as shown in Table 1.

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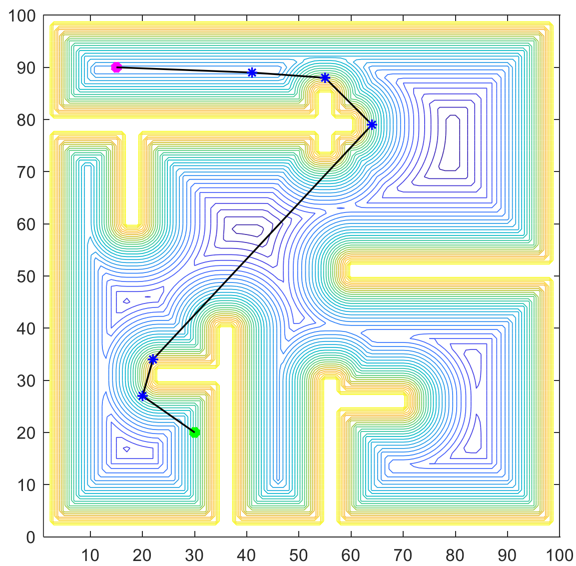
Table 1. *Parameter table*

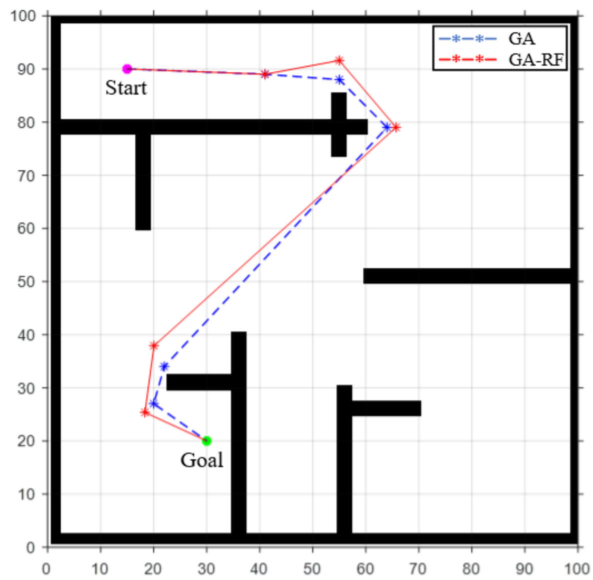
Algorithm	Parameter	First scenerio	Second scenerio
Genetic algorithm	Population size	$N = 30$	$N = 30$
	Crossover rate	$P_c = 0.8$	$P_c = 0.8$
	Mutation rate	$P_m = 0.2$	$P_m = 0.2$
	Max generation	1000	1000
Potential field	Threshold of the RPF	$Q^* = 5$	$Q^* = 3$
Dubins curve	Radius of the Dubins curve	$r = 4$	$r = 2$

Because of the large amount of computation so the population size of the generation should be small to satisfy the computation time, as choosing 30 and 1000. The path obtained from GA is shown in Figure 13. The total path length is 133.82 units, the corresponding fitness is 0.0075, and the time to find the path is 122.87 s at the 744th generation.

The threshold of the RPF, in this case, is 5 units because if it is smaller, the path is not comfortable to move, and if it is larger, the path length is so long and not optimal for mobile robots. This parameter should be chosen based on the map and the goal of the users. Figure 14(a) shows the nodes within the influence of the RPF. These nodes recalculated their coordinate based on the distance to the obstacle and the direction of the RF effect on that node. A new path with nodes far away from the obstacle replaces the old path, which improved obstacle avoidance, as illustrated in Figure 14(b), but it has many sharp turns.



(*a*)



(*b*)

Figure 14. *(a). The repulsive potential field effect on nodes. (b). The improved path by repulsive force*

Due to the nonholonomic constraints in the Car-like mobile robot model, the path must be smoothed when turning left or right. Figure 15 illustrates the effect of the Dubins curve on the path obtained from GA-RF in which the red curves replace sharp turns by using the Dubins curve method with the same radius. The radius chosen in this case is 4 units because there are a lot of free areas, and the distance between two obstacles is far, so it helps the car be more comfortable to move. This parameter also chooses by simulation and testing. The total time to find this final path is 123.52 s.

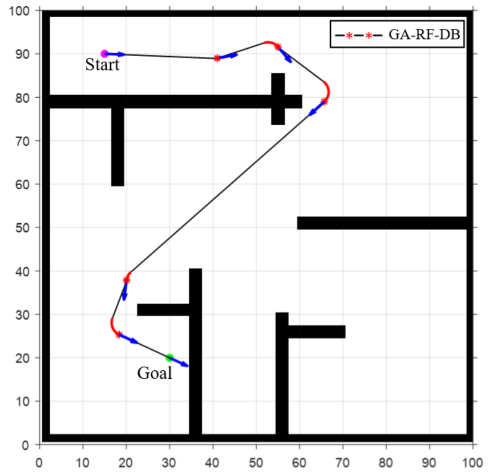


Figure 15. *Remove sharp turns with Dubins curve*

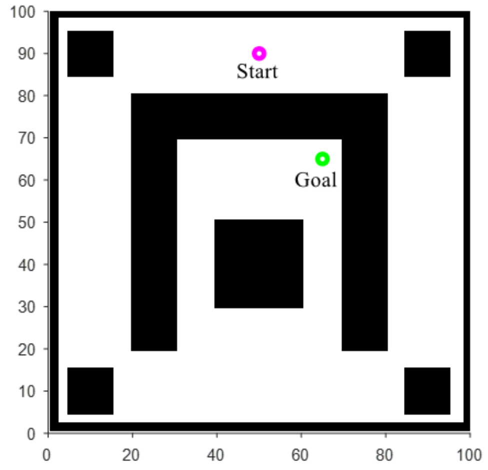


Figure 16. *Complex map in second scenario*

The final path obtained from the proposed method makes the motion of the Car-like mobile robot model efficient, improving obstacle avoidance and travelling as little distance as possible.

4.2. Second scenario: complex map with narrow space

In the second scenario, the 2D map is also set with a size is 100x100 units but more complex and hard to find a feasible path. This map is shown in Figure 16.

The parameters are used from Table 1 with the second scenario. The total path length is 157.846 units, the corresponding fitness is 0.0063, and the time to find the path is 632.260 s at the 803th generation. In this scenario, the calculation time is greater because there are more obstacles and less free space, but the distance is also the shortest path illustrated in Figure 17(a).

The threshold of the RPF and the radius of the Dubins curve is smaller than in the first scenario due to the obstacle being near each other, especially three for the threshold of RPF and two for the radius of the Dubins curve. The result is shown in Figures 17(b) and 17(c).

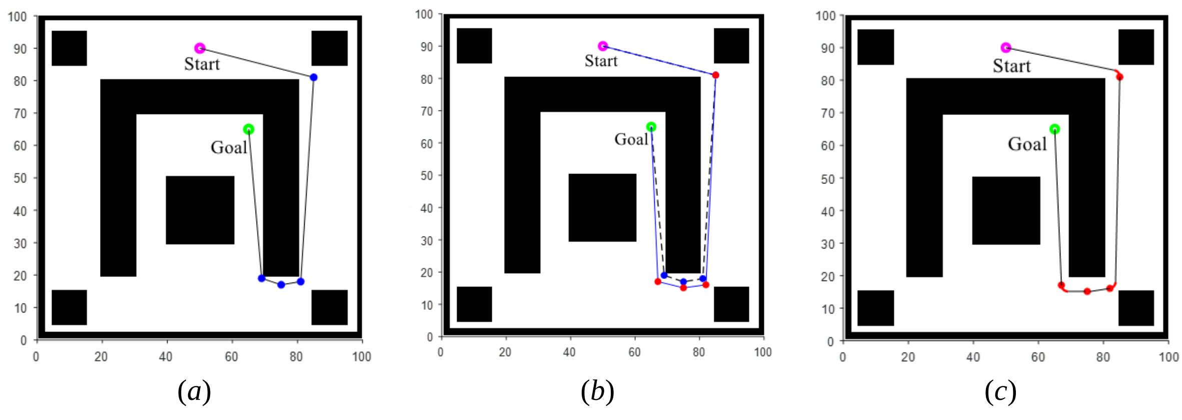


Figure 17. *The path planning obtained by GA (a). The path planning using GA and PF (b). The optimal path planning using combined method (c)*

Two scenarios show that the proposed method is suitable for finding the optimal path in several distinguished environments. However, if the structure of the environment is complex and complicated, it takes time to compute the shortest path.

5. Conclusions

In this study, a new method is proposed based on the combination of the genetic algorithm, potential field, and Dubins curve to solve the optimal smooth-path motion planning problem for a Car-like mobile robot with nonholonomic constraints. The results of simulation and testing on MATLAB show that the proposed method successfully finds the shortest feasible path planning by GA. In addition, the nonholonomic constraint in the Car-like mobile robot model is considered by the Dubins curve. The ability to avoid obstacles in the environment is also improved through the application of RF from PF. However, the period of finding random paths at population initialization in GA is thoroughly time-consuming. Therefore, the proposed method can be further enhanced by combining it with a new population initialization method. This work is an important part of building a fully autonomous navigation system in practice, whether it is enhanced with the abilities of dynamic obstacle avoidance, localization, and mapping. So, the research is a fundamental resource for other works in the future.

Acknowledgments

This research was implemented at the Robotics and Intelligent Control Laboratory (RIC Lab), Faculty of Electrical and Electronics Engineering, Ho Chi Minh City University of Technology and Education, Vietnam. We sincerely thank the support of all members of RIC Lab.

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JTE HCMUTE
ISSN: 2615-9740
JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Education
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