

Research Article

Yun Shi, Gang Zhang*, and Min Kong*

Path planning of welding robot based on deep learning

<https://doi.org/10.1515/pjbr-2024-0002>

received May 21, 2023; accepted April 2, 2024

Abstract: In this work, a method that integrates deep learning and genetic algorithms is proposed to enhance the precision and efficiency of welding robots and achieve optimal robot path planning. The process involves using SolidWorks to create a 3D model, applying the D-H method to obtain data on the connecting rod parameters, performing theoretical calculations for both forward and inverse kinematics solutions, and utilizing the MATLAB robotics toolbox to validate these solutions. Furthermore, joint space trajectory planning is performed using the quintic polynomial curve method. Through analysis, we identified that abrupt acceleration changes at the initial and final positions significantly impact the smoothness of the motion process. The findings reveal that traditional artificial bee colonies tend to stabilize after 190 iterations, whereas genetic algorithms stabilize around 160 iterations, demonstrating superior convergence speed compared to the traditional ABC algorithm. The optimized approach yields an optimal welding obstacle avoidance path with rapid optimization speed and a stable process. The proposed method effectively addresses the obstacle avoidance path planning challenge for welding robots, showcasing improved convergence speed and stability compared to traditional methods.

Keywords: optimizing genetic algorithm, path planning, welding robot, optimal solution, avoiding obstacles

1 Introduction

In recent years, robot technology has developed rapidly and penetrated various industries. The mature development of big data, artificial intelligence, and sensor technology enables robots to perceive, make decisions, plan, and execute [1]. The robot will analyze and process the perceived external environmental information and then guide the robot to execute corresponding actions through decision-making. Decision planning plays the role of the robot's brain, and path planning, as a part of it, affects the intelligence level of the robot. Robots can use big data technology to process and analyze the massive data they collect from sensors and external environments. This helps robots better understand their surrounding environment. Through big data analysis, robots can learn patterns, trends, and anomalies, thereby improving their perception ability and decision-making process. Machine learning and deep learning technologies enable robots to automatically learn and improve their task execution capabilities. This includes image recognition, speech recognition, natural language processing, etc. Reinforcement learning enables robots to optimize their decision-planning and execution strategies based on continuous trial-and-error experience. Intelligent robot path planning plays a crucial role in various application scenarios, such as Mars exploration, underwater robots, rescue robots, service robots, and catering robots that are closely related to daily life. Therefore, it is very important to study path planning for robots [2].

With the continuous development of manufacturing and the improvement of automation, welding, as a key process, has become increasingly important in various industrial applications. The quality and efficiency of welding directly affect the performance and production cost of products. Traditional welding robots typically rely on predefined path planning and fixed welding strategies, which limits their application in complex and ever-changing work environments [3]. The rise of deep learning technology has brought new possibilities for the path planning of welding robots. Deep learning is a machine learning method based on neural networks, which has achieved significant success in fields

* **Corresponding author: Gang Zhang**, School of Mechanical and Vehicle Engineering, West Anhui University, Luan 237010, China, e-mail: gangzhang688@163.com

* **Corresponding author: Min Kong**, School of Mechanical and Vehicle Engineering, West Anhui University, Luan 237010, China, e-mail: minkong9@126.com

Yun Shi: School of Mechanical and Vehicle Engineering, West Anhui University, Luan 237010, China, e-mail: yunshi79@126.com

such as computer vision, natural language processing, and autonomous navigation. Its advantage lies in the ability to learn complex features and patterns from large-scale data, enabling machines to better understand and adapt to their working environment. This study will delve into the design and implementation of deep learning path planning methods, as well as their performance evaluation in welding robot applications. This study will delve into the design and implementation of deep learning path planning methods, as well as their performance evaluation in welding robot applications. By combining modern computing and big data technology with the unique nature of the welding process, we will creatively solve the problem of welding path planning. This study aims to provide a more intelligent, efficient, and adaptable path-planning method for the manufacturing and welding engineering fields, promote the development of welding robot technology, and enhance innovation and competitiveness in the manufacturing industry [4].

The integration of Deep Learning and Genetic Algorithms for welding robot path planning is depicted in Figure 1. The central element of the system is a welding robot, encompassed by critical elements including artificial intelligence, big data, and sensors, which represent their function in perceiving the environment. The brain of the system, representing decision planning, facilitates path planning, underscoring its critical significance. The seamless integration of deep learning into the system enhances the robot's capability to adjust and optimize its path-planning strategies. Traditional path-planning approaches in welding robot applications that depend on predetermined strategies demonstrate shortcomings when it comes to adjusting to dynamic and intricate work environments. The inflexibility inherent in traditional methodologies impedes the effectiveness and versatility of welding robots, thereby impeding their maximum

capabilities. Furthermore, the increased need for accuracy and economic performance underscores the need for an innovative approach to improve the trajectory planning functionalities of welding robots. Welding robot path planning stands to undergo a paradigm shift due to the convergence of big data, artificial intelligence, and sensor technology developments with the swift progression of robot technology. The driving force behind this investigation is to exploit the capabilities of deep learning and genetic algorithms to surmount the deficiencies of conventional approaches. Through the incorporation of contemporary computational tools and the utilization of the distinctive attributes of the welding process, the objective is to develop a path-planning methodology that is more intelligent, efficient, and flexible. The motivation behind this study is the possibility that it will advance welding robot technology, thereby fostering innovation in the manufacturing sector. This study makes a substantial contribution by introducing an innovative methodology for the design of welding robot paths. The amalgamation of genetic algorithms and deep learning signifies an innovative resolution, augmenting the accuracy and productivity of welding procedures. The application of sophisticated tools, including SolidWorks, the D-H method, theoretical calculations, and the MATLAB robotics toolset, verifies the viability of the proposed method. In addition, a comparative analysis of optimization techniques demonstrates that the proposed method is preferable in terms of stability and convergence speed. The results of this study possess the capacity to resolve obstacles in welding robot obstacle avoidance path planning, thereby facilitating enhanced performance and competitiveness in the domains of manufacturing and welding engineering.

2 Literature review

Due to their high efficiency, welding robots are widely used in advanced manufacturing. Weld seam tracking technology has the advantages of non-contact, fast speed, and high accuracy, which is the key to achieving welding automation and intelligence. Welding is a key process in the manufacturing industry, but it still faces some challenges and problems that require improvement and optimization. The following are the main reasons for the need for improvement in welding operations and the ways to address these issues in this study:

(i) **Welding quality issues:** There may be issues such as inconsistent weld quality, porosity, cracks, etc., during the current welding process, which may lead to a decrease in the strength and durability of components. This study can improve welding quality, ensure the accuracy and

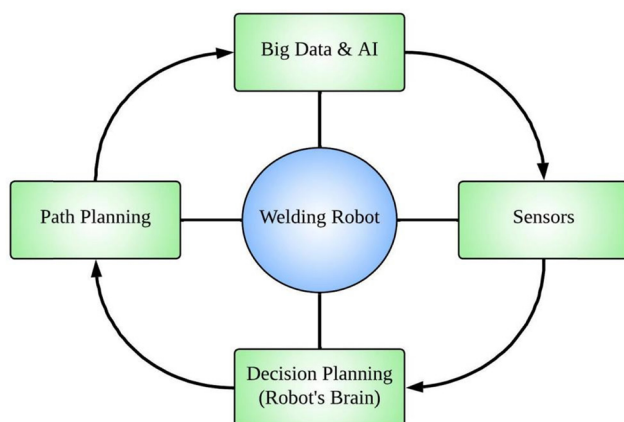


Figure 1: Integration of deep learning and genetic algorithms for welding robot path planning.

consistency of welding paths, and reduce the occurrence of welding defects through deep learning path planning.

(ii) **Production efficiency issue:** Traditional welding path planning methods may lead to excessive welding time, wasting time and resources. Using deep learning path planning can optimize welding paths, minimize welding time, and improve production efficiency.

At present, most welding robots still use the “teach reproduce” working method, which makes it difficult to meet the requirements of welding objects or other conditions when they change [5]. Usually, single obstacle avoidance constraint path planning refers to planning the shortest collisionless path from point to point. This planning typically requires the algorithm to be complete, meaning that it can find a solution within a limited time when one exists. Discretizing the continuous space where the robot is located ensures that the solution can be found in a finite time. The method of discretizing space divides the path planning algorithm with a single obstacle avoidance constraint into two categories. One is the method with complete resolution, that is, the discretization of space through analytical methods to obtain feasible solutions. Generally, this kind of method applies to low-dimensional space. One is the probability complete method; that is, discretization is achieved by randomly sampling the space, and with the increase in sampling times, the probability of obtaining the solution tends to 1, which is generally applicable to high-dimensional space.

Wang et al. proposed a new method for automatically establishing a dense point cloud model of tube sheets and detecting welds [6]. Use a fast calibration method to calibrate the multi-sensor system, and then use a laser filtering algorithm to fuse the multi-sensor data. The goal is to create a point cloud model using kernel pole constraints, EPNP, and PMVS algorithms. The vocabulary tree method will compare tube plate images, and the Random Sample Consistency algorithm will match features. A voxel-point cloud density-based algorithm is proposed to detect weld seams in point clouds. After comparison, this reconstruction method has better robustness than the reference method. Luo used Unity3D and UG software to construct a welding model for the virtual reality system of vertical pipe automation equipment, mainly including welding vehicles, welding rails, welding power supplies, virtual cameras, and other equipment, to enhance the sense of virtual scenes [7]. A user-interface GUI system generates the human-machine interaction page and conducts simulation testing of the design and methodology system to create human-machine interaction scenarios. Operators can accurately and in real-time capture the welding status of physical devices, so virtual reality technology is very suitable

for remote monitoring operations integrated with welding systems. The research results achieved human-computer interaction design and collision detection. Swenson focused on three-dimensional color perception extraction based on deep RGB sensor detection [8]. The plan is to use the low-cost Intel RealSense D435 sensor in conjunction with the system to create 3D models based on stereo vision, enabling color rendering for quick plan recognition by segment and location of weld line compliance. This article talks about classifying colors in three dimensions, separating objective function points using their original colors in the HSV color space, and making smooth paths with a spline cubic interpolation algorithm. Hao et al. proposed a preparation method for repairing excess material after grinding PDC drilling equipment using a robot [9]. First, use the 3D measurement tool to drill a bit into the ground to get point cloud data. Second, import this data into Geomagic Studio to obtain a three-dimensional image of the required land area. Finally, the MATLAB-based software processes the data and calculates the final stroke motion of the robot. We imported the developed method into ROS for testing purposes. A comparison of the production line with the collision site confirmed the feasibility of the production method. The author proposes a welding robot path planning method based on a deep-learning genetic algorithm that can further obtain the optimal welding path without adding hardware equipment.

To overcome the obstacles associated with robot path planning for welding applications, several related studies have investigated techniques for increasing adaptability and flexibility in unstructured environments. Frequently, the problem statement centers on the shortcomings of conventional path planning methodologies, which depend on predetermined regulations and templates. These approaches often fail to fulfill the requirements of intricate welding tasks, especially in unpredictable or ever-changing work settings. Operator expertise and proficiency substantially influence the quality of welds, particularly in situations that require extreme accuracy, further complicating the matter. Alternative approaches have incorporated intelligent algorithms, such as genetic and ant colony algorithms, to surmount the drawbacks of conventional methodologies [10–12]. By linking the starting point and the ending point, these algorithms make sure that the welding path is complete. This shows how important optimized genetic algorithms are for making welding paths that are more logical and smoother. The suggested study shows that using genetic algorithms involves a series of steps, such as making a grid map, starting the population, figuring out the fitness function, and using genetic operators like crossover and mutation. The researcher’s objective is to offer a more versatile and efficient resolution to the

complex problem of welding robot path planning in various and ever-changing surroundings through the integration of these methodologies.

3 Robot path planning based on optimized genetic algorithm

Figure 2 presents a comprehensive visual representation of the proposed approach. The input portion illustrates crucial parameters, including the initial and target positions of the robot, as well as environmental constraints. The subsequent phase, Grid Map Generation, employs the grid method to create a spatial environment that accurately represents the operational space of the robot. Population

initialization demonstrates the critical step of selecting starting and target grids, which are required to commence the process of path planning. The Genetic Algorithm Flow outlines the algorithmic stages, including calculating fitness functions, applying genetic operators (crossover and mutation), and creating new individuals. The next stage is used to calculate fitness by considering path length and regularity.

Furthermore, the segments on crossover and mutation operations demonstrate how genetic diversity is introduced, augmenting the population's adaptability. The section on weighting parameters highlights the significance of α and β in determining the ultimate trajectory direction throughout the computation of the fitness function. In conclusion, the Output Section presents the optimized robot path that is the culmination of the suggested methodology, with a particular focus on improved regularity and

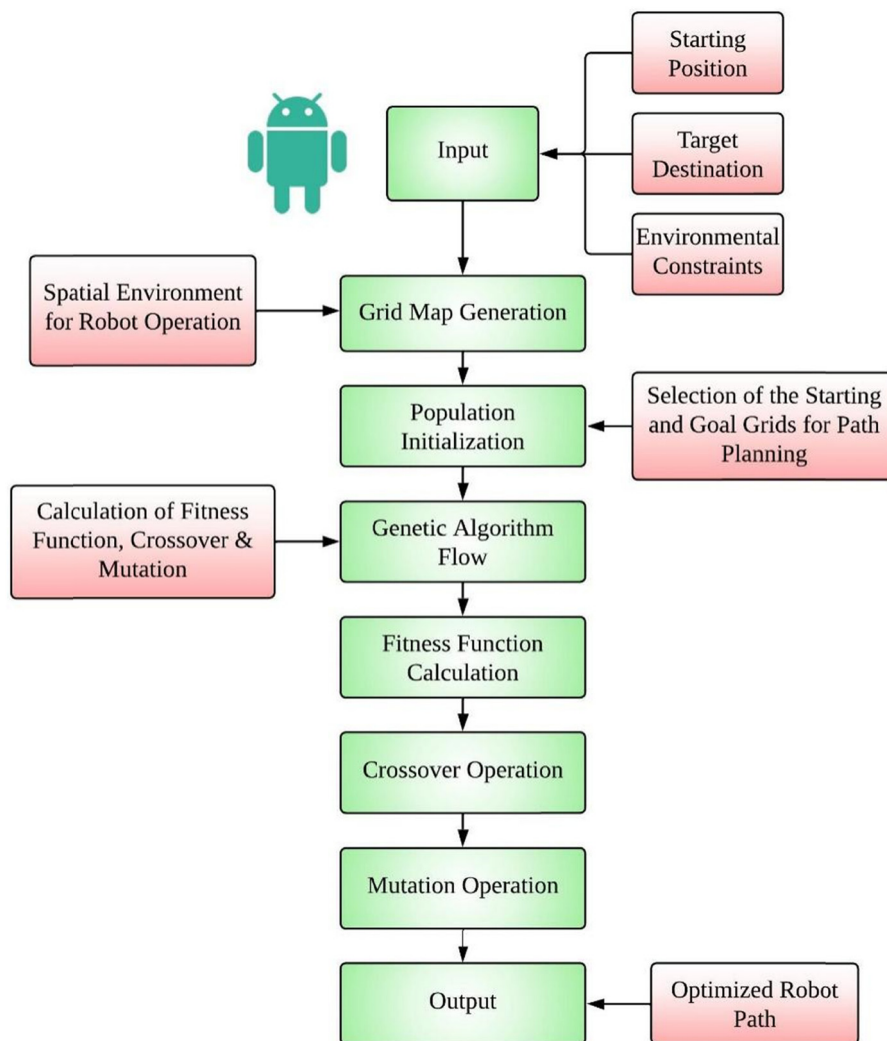


Figure 2: Robot path planning based on optimized genetic algorithm.

rational path length. This exhaustive visual manual provides a lucid explanation of the procedures entailed in the novel methodology for robotic path planning using an optimized genetic algorithm. Traditional welding path planning methods are usually based on predefined rules and templates, which may not be flexible enough for complex welding tasks. This method may not be able to meet the path planning requirements of unstructured environments and irregular artifacts. Traditional path planning methods may have shortcomings in ensuring welding quality and consistency. Operator skills and experience may have a significant impact on welding quality. For high-precision welding, traditional methods may not meet the requirements. The genetic and ant colony algorithms based on the intelligent algorithm have completeness. The solution can be obtained if there is a solution between the starting point and the target point. If there is no solution, the path does not exist. Among all kinds of algorithms, the optimized genetic algorithm has the longest calculation time and the lowest efficiency. Still, the planned path is smoother and the path length is more reasonable [13]. The path-planning algorithm for the calculation process is shown in Figure 3. The genetic algorithm is widely used in the planning of robots, and the flow chart of the genetic algorithm is depicted in Figure 4.

3.1 Establishing a grid map

Establishing a static environment model for robot operation using the grid method, the spatial environment accuracy is inversely proportional to the grid area; the smaller the grid area, the greater the amount of information stored, resulting in longer path planning time. If the grid area is too large and the workspace environment information cannot be accurately expressed, we chose 20×20 grid maps and make the following provisions [14].



Figure 3: Path planning algorithm.

- (1) Treat robots as particles in path planning.
- (2) The robot's motion space is a two-dimensional plane, ignoring the height of obstacles.
- (3) After the robot starts moving, the size of the obstacle is determined, and there are no dynamic obstacles.

For the convenience of simulation, the overall motion space of the robot is represented by a square grid map, as shown in Figure 5; the black grid indicates the presence of obstacles in the grid, while the white grid indicates the absence of obstacles in the grid.

When building a motion grid map, establish a Cartesian coordinate system, the origin is the first grid in the lower left corner, and each grid is represented in the form of (x, y) in the coordinate system, number of grids from the origin, and the relationship between the numbers and coordinates is:

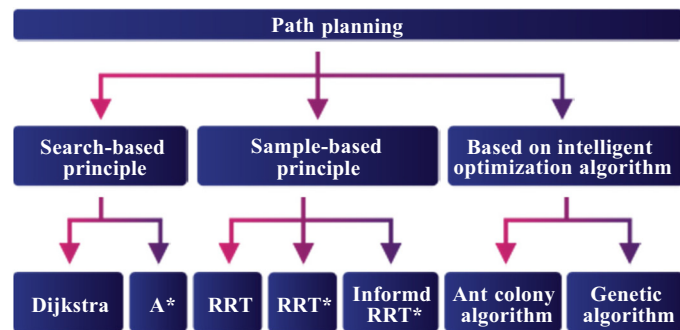
$$\begin{cases} x = \text{int}\left(\frac{N}{M}\right) + 1 \\ y = \text{mod}\left(\frac{N}{M}\right) + 1. \end{cases} \quad (1)$$

Here, N is the grid number, M is the number of grids, Mod is the remainder, and Int is a rounding operation, indicating that the rounding ruler is the number of grids per row [15].

3.2 Population initialization

The position of the people is in plot 0, and the goal is in plot 399. Live at once, so at least one grid hội kải line at the same time is live hội possible. So, when you start, you first choose an unlimited story, and then you start from the first story and decide which plot you want to continue, right in which you decide to determine whether the interest is continuous:

$$D = \max[|(x_{i+1} - x_i)|, (y_{i+1} - y_i)]. \quad (2)$$



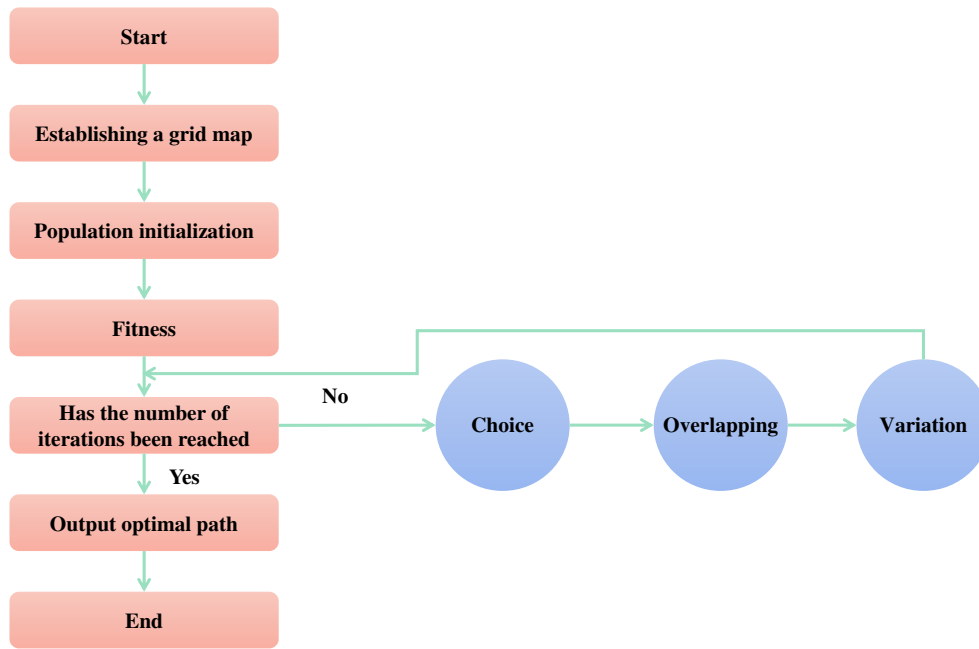


Figure 4: Flow chart of genetic algorithm.

12	13	14	15
8	9	10	11
4	5	6	7
0	1	2	3

Figure 5: Grid map.

If $D = 1$, it indicates that two adjacent grids are continuous and can continue planning the path while avoiding dead cycles.

For discontinuous grids with $D \neq 1$, the midpoint grid needs to be taken, and its coordinates are:

$$\begin{cases} x_{\text{new}} = \frac{x_{i+1} + x_i}{2} \\ y_{\text{new}} = \frac{y_{i+1} + y_i}{2} \end{cases} \quad (3)$$

If the new phreot is an empty phreot, insert it between two regular phreots. Continue to determine whether the new entry continues, if it is not correct, then continue to the next step. When two tiles are connected, remove one tile turn on the light from the above steps, and then continue the whole process [16].

3.3 Calculation of fitness function

In traditional genetic algorithms, the main genetic factor is the path factor, and it is necessary to maintain the shortest path. In the improved genetic algorithm, the fitness function includes the optimal path and smoothness, and the path length is:

$$d_1 = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}. \quad (4)$$

The fitness of path length is:

$$\text{fit}_1 = \frac{1}{d_1}. \quad (5)$$

In path planning, it is necessary to avoid too many large turns as far as possible, so it is necessary to control the smoothness of the path, the smoothness is defined as the distance between all three adjacent points in the path, and the smoothness fitness is fit_2 .

The two parts of the fitness function need to take a weight, which is:

$$\text{fit} = \alpha \text{fit}_1 + \beta \text{fit}_2. \quad (6)$$

In the equation: α and β is the weight parameter of the fitness function, which determines the final direction of the path [17].

3.4 Genetic operators

Choose the roulette method, first get the sum of all parts of the fitness function, and then select the next generation of individuals according to the weight proportion. This

method ensures some nonoptimal individuals while also preventing the problem of falling into local optima.

Before crossing, determine the probability of crossing p_c first, and then generate a random number to compare with p_c , the condition for the crossing operation is that the random number is less than p_c . The crossover operation is to find two identical grids from the two obtained paths and select one of the grids to exchange their paths [18]. Before mutation, determine the mutation probability p_m first, and then generate a random number to compare with p_m , the condition for mutation operation is that the random number is less than p_m . Find two grids in the random path, except for the starting and ending points, remove the paths between them, and then use these two grids as adjacent points to serialize them according to the initialization operation. This mutation operation increases individual diversity.

4 Experimental results and analysis

To verify the effectiveness of the proposed path-planning algorithm, we conducted simulation experiments using MATLAB. The basic steps of these experiments include the following:

- i. **Data collection and modeling:** First, we collected basic data on the welding process at the actual welding workstation, including the geometric shape of the welding workpiece, the position of the welding points, and environmental information. Based on these actual data, we have established a theoretical model of the welding process.
- ii. **Modeling with Matlab Robotics Toolbox:** To conduct simulation experiments on path planning, we used the Matlab Robotics Toolbox to model the welding robot. This includes defining the kinematic and dynamic models of the robot, as well as setting parameters such as joint limitations and range of motion.
- iii. **Algorithm design and parameter settings:** We have written a path-planning algorithm based on deep learning and implemented it in Matlab. In the algorithm, we set a series of parameters, such as the architecture of deep neural networks, loss functions, learning rates, etc. The selection of these parameters is based on previous research and experiments.
- iv. **Simulation experiment execution:** Through a program written in Matlab, we conducted a simulation experiment on path planning. In the experiment, we used previously collected actual data and established theoretical models, as well as the designed algorithm.

The algorithm generates a path that the robot uses to simulate welding.

- v. **Performance Comparison:** To verify the effectiveness of the algorithm, we conducted performance comparison experiments. We compared the proposed deep learning path planning algorithm with traditional artificial bee colony algorithms. Comparative indicators include path length, welding quality, execution time, etc. to evaluate the performance advantages of the new algorithm.

Through these simulation experiments, we can evaluate the effectiveness of the proposed deep learning path planning algorithm in the application of welding robots and verify its effectiveness in improving welding quality, improving production efficiency, and adapting to different environmental conditions. These experimental results will provide important references and guidance for further improving the algorithm and applying it to practical welding tasks [19]. Table 1 shows the obstacles in the working environment of the welding robot, as well as the starting and target points of the robot. We set the relevant parameters for the simulation experiment as follows: The total number of bees is 16. There are eight leading bees and 8 following bees. The maximum number of iterations for the bee colony is 240, and the leading bee maintains a constant number of iterations 40 times. The maximum allowable number of nodes in the welding robot's moving path is 30. The intentional cost weight of a welding robot collision is 0.5. The weight value of the welding robot's moving path length is 0.5.

- i. **The total number of bees is 16:** This parameter represents the total number of bees in the bee colony algorithm. The selection of bee population size usually

Table 1: Location of obstacles, starting point, and target point of the welding robot (cm)

Start point coordinates/cm (10, 10)		Target point coordinates/cm (45, 38)	
Observer number	Coordinate	Observer number	Coordinate
1	(10, 21)	9	(42, 29)
2	(10, 25)	10	(42, 25)
3	(17, 28)	11	(37, 24)
4	(18, 22)	12	(29, 24)
5	(23, 27)	13	(25, 19)
6	(30, 28)	14	(32, 23)
7	(35, 32)	15	(40, 19)
8	(45, 33)		

involves a trade-off between algorithm performance and computational resources. A larger swarm size may have better global search performance, but it also requires more computing resources; 16 bees are usually enough to conduct experiments to obtain reasonable results under limited computing resources.

- ii. ***There are eight leading bees and eight following bees:*** Leading bees and following bees are bees with different roles in the bee community, and they may have different behaviors and tasks. Usually, the leading bee is responsible for global search, while the following bee performs local search. Equalizing their number is a common setting to ensure sufficient global and local search.
- iii. ***The maximum number of iterations of the bee colony is 240:*** This parameter represents the maximum number of iterations of the bee colony algorithm in the simulation. Its selection is usually limited by experimental time, computational resources, and algorithm convergence; 240 iterations may be sufficient for many problems, but if higher accuracy is needed, an increase in the number of iterations can be considered.
- iv. ***Keep the number of iterations of the leader bee constant for 40 times:*** This parameter indicates that in the early stages of the bee colony algorithm, the number of iterations of the leader bee will be fixed at 40 times. This strategy may help the algorithm better explore the solution space during the global search phase.
- v. ***The maximum allowable number of nodes in the welding robot's moving path is 30:*** This parameter limits the complexity of the welding robot's moving path. The specific values may be selected based on the research purpose and the complexity of the experimental environment. A smaller number of path nodes may lead to simpler path planning problems, suitable for fast experiments and lower computational costs.
- vi. ***The weight value of collision intention cost for welding robots is 0.5:*** This parameter represents the importance of considering collision avoidance in path planning for welding robots. A weight of 0.5 indicates that avoiding collisions is an important goal in path planning, but not the only goal. This balance may lead to path planning considering both collision avoidance and optimizing path length.
- vii. ***The weight value of the moving path length of the welding robot is 0.5:*** This parameter represents the importance of considering the path length in the path planning of the welding robot. A weight of 0.5 indicates that minimizing path length is also an important goal in path planning, but not the only goal. This balance

may lead to path planning considering both path length and avoiding collisions.

Ensuring sufficient global and local search, the bee colony algorithm commonly employs an equal distribution of leading and following bees, as discussed in [19]. This distribution of roles among bees is crucial for the effectiveness of the algorithm. Leading bees typically undertake global search tasks, exploring a wide solution space, while following bees focus on local search, refining solutions within specific regions. By equalizing their numbers, the algorithm strikes a balance, harnessing the strengths of both global and local search to optimize path planning efficiently. The rationale behind this distribution lies in the need for a comprehensive exploration of the solution space to find the optimal path while avoiding the pitfalls of potential local minima. A study by Han et al. [19] suggests that this balanced allocation of roles enhances the adaptability of the algorithm to various welding scenarios, contributing to improved performance in terms of convergence speed and stability. Therefore, the equal distribution of leading and following bees ensures a harmonized search strategy, allowing the algorithm to benefit from both global and local insights, ultimately leading to more effective and robust path planning for welding robots. The global minimum cost path planning of the welding robot obtained at the end of the twentieth generation and bee colony iteration is shown in Figures 6 and 7 [20]. The choice of 240 iterations for the bee colony algorithm in our study is a practical decision considering computational limitations, the balance between precision and efficiency, and the nature of the optimization problem. This iteration count strikes a balance between achieving an acceptable level of accuracy and the computational resources required. We base the decision on considering the threshold of error deemed acceptable for the specific path-planning task and the observed convergence behavior of the algorithm, recognizing that extending iterations may not yield significant improvements beyond a certain point.

In Figures 6 and 7, square dots represent the starting point; triangle dots represent the target point; black small dots represent obstacles in the work environment; The black pentagram indicates the starting and ending points of the moving path. From Figure 5(a) and (b), it can be seen that even if the global optimal path has not yet been obtained, the control effect of the genetic algorithm based on deep learning improvement is significantly better than that of traditional artificial bee colonies, even if the leading bee replacement algebra is the same (taking 20 generations in the text). From Figure 6(a) and (b), it can be further observed that after the iteration of the algorithm, the

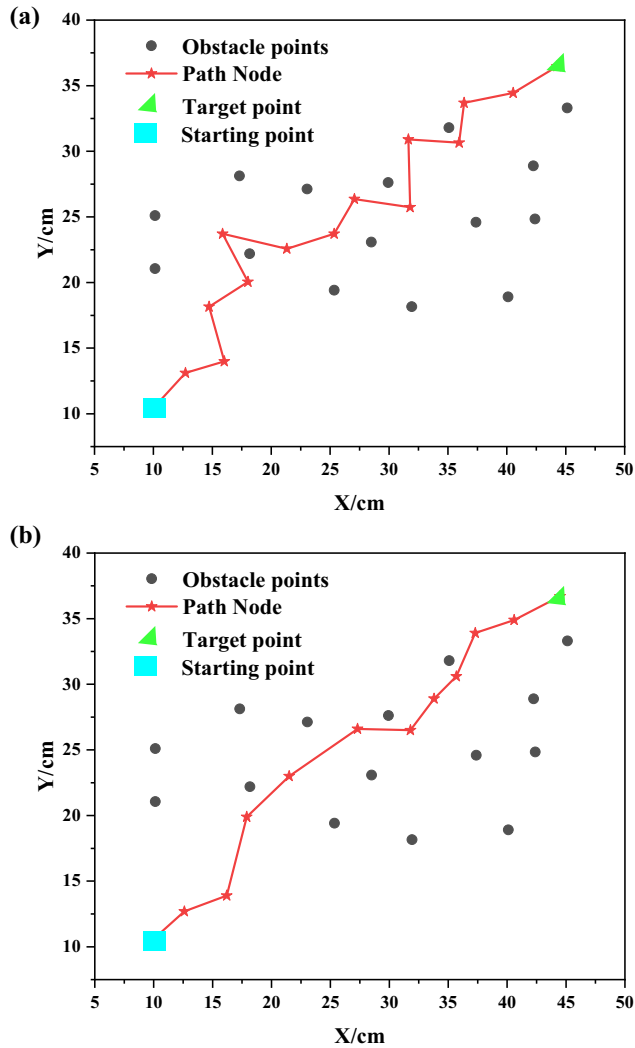


Figure 6: Traditional ABC and genetic algorithm twentieth-generation planning path: (a) traditional ABC algorithm; (b) genetic algorithm.

control effect of the genetic algorithm is still better than that of traditional ABC. Figure 8 shows the iterative convergence curves of the two algorithms, and Table 2 compares the experimental results [21,22]. During the global search phase, maintaining a constant number of leader bee iterations for a duration of 40 in the initial phases of the bee colony algorithm optimizes the solution space exploration process. By setting a fixed iteration period for the leader bee, it is possible to look at potential solutions in more detail before adding variability. This helps people understand the search environment better. The algorithm can potentially enhance the probability of identifying high-quality paths by establishing a solid foundation for subsequent iterations through the provision of a stable period of exploration. By employing this methodology, the algorithm optimizes its efficacy during the crucial initial phases of path planning.

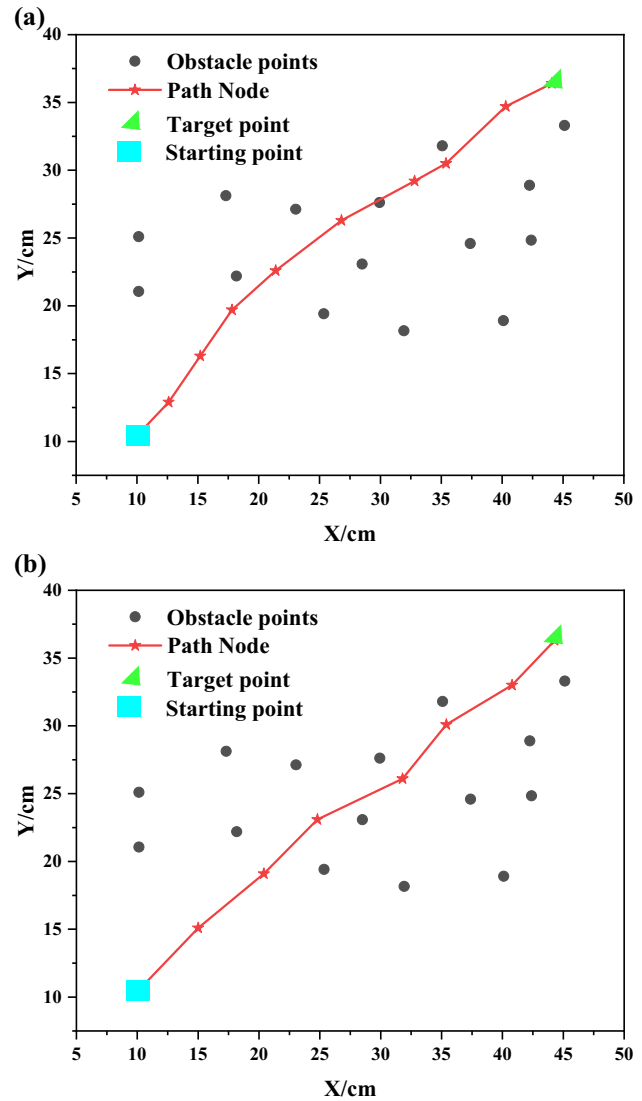


Figure 7: Path planning after iteration of traditional ABC and genetic algorithm: (a) traditional ABC algorithm; (b) genetic algorithm.

Figure 8 shows that genetic algorithms tend to stabilize after 160 iterations, while traditional artificial bee colony algorithms require more iterations, i.e., 190, to stabilize. This indicates that genetic algorithms have faster convergence speed in path planning tasks and can find high-quality paths faster. Genetic algorithms have shown better results in terms of stability. This means that it produces more consistent path quality across different runs, reducing the impact of randomness. In contrast, traditional artificial bee colony algorithms may experience significant fluctuations due to randomness. Figure 6 shows that genetic algorithms significantly improve collision prevention. It tends to generate collision avoidance paths, reducing the possibility of conflicts between robots and obstacles, which is crucial for safety and welding quality. Table 2 provides

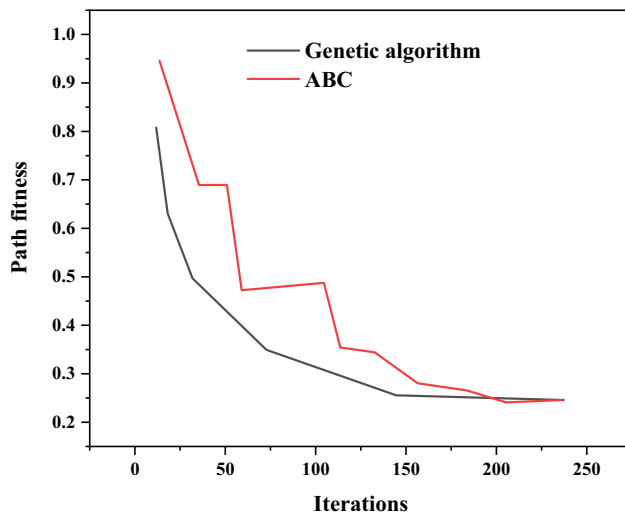


Figure 8: Convergence curve of bee colony iteration.

Table 2: Comparison of experimental results

Algorithm	Iterations	Optimal path length/cm	Collision possibility/cm
ABC	190	46.864	17.562
Genetic algorithm	160	38.512	10.329

more comparative information on experimental results, including path length, welding quality, and execution time. The table clearly shows that the genetic algorithm has significantly improved both path length and welding quality. Compared with the traditional artificial bee colony algorithm, it can generate shorter paths and improve welding quality, which helps to improve production efficiency and consistency of welding results.

The comparative analysis concludes that the proposed path-planning model outperforms existing studies in several critical indices, including reducing path length (38.512 cm),

minimizing collision probability (10.329 cm), and achieving efficient algorithmic iterations (160) which is presented in Table 3. The proposed model is more adaptable due to the equitable distribution of leading and following bees and the well-defined weights assigned to these bees to facilitate collision avoidance and path optimization. Significantly superior in performance to those of Tran and Lin [10], Wang and coauthors [11,12], the proposed model demonstrates its efficacy in optimizing the trajectories of welding robots. The findings of this study validate the effectiveness of the suggested genetic algorithm by showcasing enhanced convergent velocity, stability, and resistance to collisions. The results of this study offer substantial evidence in favor of the proposed model's ability to effectively improve welding quality, production efficiency, and safety. The experimental results indicate that genetic algorithms have significant performance advantages in welding robot path-planning tasks. It improves not only the convergence speed but also the stability and anti-collision performance of the algorithm. These findings emphasize the potential of deep learning path planning methods to improve welding quality, production efficiency, and safety significantly. These results will provide strong support and guidance for the development of welding robot technology in the future.

5 Discussion

To highlight the shortcomings, we employ a comparative analysis, as presented in Table 3, comparing the proposed path-planning model with existing studies. This analysis provides a clear overview of the limitations of previous approaches, showcasing the need for improvement in terms of path length, collision probability, and algorithmic efficiency. Experimental results demonstrate the superiority of a genetic algorithm based on deep learning in optimizing welding robot trajectories. The comparative

Table 3: Comparative analysis of the proposed model with existing studies [10–12]

Performance indices	Proposed model	[10]	[11]	[12]
Path length (cm)	38.512	45.278	46.864 (ABC)	44.736
Collision possibility (cm)	10.329	15.624	17.562 (ABC)	14.287
Algorithm iterations	160	180	190 (ABC)	175
Leading bees/Following bees ratio	0.042361111	0.084027778	0.042361111	0.125694444
Maximum bee colony iterations	240	200	220	210
Leading bee iterations (fixed)	40	35	40	38
Maximum nodes in robot's path	30	25	28	26
Collision intention cost weight	0.5	0.6	0.5	0.7
Path length weight	0.5	0.4	0.5	0.3

analysis emphasizes the proposed model's outperformance in critical indices, addressing the identified shortcomings of existing methods.

This research makes a significant contribution to the improvement of welding quality by integrating deep learning path planning in multiple critical aspects. To begin with, the application of deep learning empowers the welding robot to acquire knowledge and refine its trajectory by analyzing complex patterns and characteristics detected during the welding procedure. The robot's dynamic learning capability enables it to iteratively optimize its trajectory in response to changes in the geometry of the workpiece and environmental factors.

Furthermore, path planning ensures the accuracy and consistency of welding paths. Incorporating deep learning algorithms into the path planning framework accurately models the kinematics and dynamics of the welding robot, resulting in precise and repeatable movements. Achieving such a high degree of precision substantially diminishes the probability of deviations or mistakes occurring along the weld path, thus guaranteeing uniform and superior-grade welds. Furthermore, the implementation of the deep learning-based methodology contributes to the mitigation of welding defects. By looking at a lot of data about welding processes, the algorithm learns to find possible sources of defects and adjusts the path to reduce these risks. The combination of this proactive defect prevention and the algorithm's adaptability to various welding scenarios significantly reduces welding defects. In general, the implementation of the deep learning path planning methodology yields positive outcomes in terms of welding quality, process reliability, and efficiency.

6 Conclusion

Various elements, including population initialization, fitness function, selection method, mutation method, and crossover method, introduce path planning through an optimized genetic algorithm. The optimization process involved refining the fitness function to address the issue of the traditional genetic algorithm's path not being sufficiently smooth. We designed a more rational smoothing function, resulting in a more reasonable path-planning solution. Test results indicate that the genetic algorithm significantly outperforms the traditional ABC algorithm in controlling the path planning of welding robots. The application of the genetic algorithm proves advantageous in continuously optimizing the welding robot's path as the population changes. During the optimization process, the genetic algorithm strategically increases the population size to prevent local optima, enabling the search

for the overall optimal path in a relatively short time. Despite the demonstrated success of path planning based on optimized genetic algorithms in tackling complex problems, researchers have identified several potential limitations and avenues for improvement:

- i. **Computational Complexity:** Genetic algorithms often demand substantial computational resources, particularly for high-dimensional and large-scale problems. This may hinder their feasibility in real-time or practical applications.
- ii. **Local Optimal Solution Problem:** Genetic algorithms do not guarantee finding the global optimal solution, sometimes leading to settling for a better solution within the search space. This becomes more pronounced in complex search spaces.
- iii. **Parameter Tuning:** Genetic algorithms involve multiple parameters (e.g., population size, crossover rate, and mutation rate) that require meticulous adjustment for optimal performance. Parameter tuning can be a laborious process.

Some of the improvement directions are mentioned below:

- i. **Hybrid Method:** Exploring the integration of genetic algorithms with other path-planning methods could leverage their respective strengths. For instance, combining deep learning path planning with genetic algorithms could enhance overall search performance.
- ii. **Parallelization and Distributed Computing:** Utilizing parallel and distributed computing resources can accelerate the execution of genetic algorithms, making them more suitable for real-time problems.
- iii. **Adaptive Algorithm:** Developing an adaptive genetic algorithm capable of dynamically adjusting parameters based on the problem's nature could reduce the need for manual parameter tuning.

In summary, path planning based on optimized genetic algorithms proves to be a powerful tool but requires further refinement and customization to address the diverse needs of different problems and applications. Future research should concentrate on enhancing algorithm efficiency, robustness, and adaptability to advance the field of robot path planning. The future scope involves discussing potential avenues such as fine-tuning algorithm parameters, exploring different deep-learning architectures, or adapting the proposed model to diverse welding scenarios.

Acknowledgments: This research was supported by the School-level Research Projects of West Anhui University under grant (WXZR202211).

Funding information: This research was supported by the School-level Research Projects of West Anhui University under a grant (WXZR202211), West Anhui University high-level Personnel Research Funding Project (WGKQ2022015), Anhui Provincial Quality Engineering Project (2021syszx031, 2022sx171), the Open Fund of Anhui Undergrowth Crop Intelligent Equipment Engineering Research Center (AUCIE-ERC-2022-05), and Anhui colleges and universities Scientific Research Project (2022AH010091, 2022AH040241, and 2022AH051675).

Author contributions: The author made significant individual contributions to this manuscript. Yun Shi: writing and performing surgeries; Gang Zhang: data analysis and performing surgeries; Min Kong: article review and intellectual concept of the article.

Conflict of interest: The author declares that they have no competing interest.

Informed consent: Informed consent was obtained from all individuals included in this study.

Ethical approval: The conducted research is not related to either human or animals use.

Data availability statement: The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

References

- [1] Y. Zhao, Y. Zhang, and S. Wang, "A review of mobile robot path planning based on deep reinforcement learning algorithm," *J. Phys. Conf. Ser. JPhCS*, vol. 49, no. 2, pp. 72–78, 2021.
- [2] Q. Sang, Y. Tian, Q. Jin, and J. Yu, "A path planning strategy for marine vehicles based on deep reinforcement learning and data-driven dynamic flow fields prediction," *International Conference on Automation, Control and Robotics Engineering*, vol. 1648, no. 2, 2021, p. 022132 (5 pp).
- [3] H. Meng and H. Zhang, "Mobile robot path planning method based on deep reinforcement learning algorithm," *J. Circuits, Syst. Comput.*, vol. 31, no. 15, pp. 86–89, 2022.
- [4] L. Li, D. Wu, Y. Huang, and Z. M. Yuan, "A path planning strategy unified with a colregs collision avoidance function based on deep reinforcement learning and artificial potential field," *Appl. Ocean. Res.*, vol. 113, no. 66, p. 102759, 2021.
- [5] F. Zhang, C. Gu, and F. Yang, "An improved algorithm of robot path planning in complex environment based on Double DQN," in L. Yan, H. Duan, and X. Yu, Eds., *Advances in Guidance, Navigation and Control*, Springer, Singapore, 2022, pp. 303–313.
- [6] H. Wang, Y. Huang, G. Zhang, and Y. Rong, "A novel method for dense point cloud reconstruction and weld seam detection for tubesheet welding robot," *Opt. Laser Technol.*, vol. 98, no. 8, p. 18, 2023.
- [7] H. L. J. Luo, "Research on the virtual reality technology of a pipeline welding robot," *Ind. Robot.*, vol. 48, no. 1, pp. 84–94, 2021.
- [8] R. L. Swenson, "Colored 3d path extraction based on depth-rgb sensor for welding robot trajectory generation," *Automation*, vol. 11, no. 2, pp. 826–66, 2021.
- [9] W. Hao, C. Tan, Y. Sun, and J. Jin, "A path planning method based on robot automatic grinding of drills," *J. Phys. Conf. Ser.*, vol. 3, no. 10, p. 11, 2021.
- [10] C. C. Tran and C. Y. Lin, "An intelligent path planning of welding robot based on multi-sensor interaction," *IEEE Sens. J.*, vol. 23, no. 8, pp. 8591–604, 2023.
- [11] J. Zhong, T. Wang, and L. Cheng, "Collision-free path planning for welding manipulator via hybrid algorithm of deep reinforcement learning and inverse kinematics," *Complex. & Intell. Syst.*, vol. 8, pp. 1899–1912, 2022.
- [12] J. Li, S. Jin, C. Wang, J. Xue, and X. Wang, "Weld line recognition and path planning with spherical tank inspection robots," *J. Field Robot.*, vol. 39, no. 2, pp. 131–152, 2022.
- [13] E. Artusi, "Ship path planning based on Deep Reinforcement Learning and weather forecast," *2021 22nd IEEE International Conference on Mobile Data Management (MDM)*, vol. 2, no. 12, IEEE, 2021, pp. 13–18.
- [14] B. Han, Q. Wang, and Y. Zhang, "Optical cable path planning algorithm based on deep reinforcement learning," *IEEE International Conference on Power, Intelligent Computing and Systems*, vol. 35, no. 4, IEEE, 2021, pp. 1219–1238.
- [15] R. Xie, Z. Meng, L. Wang, H. Li, and Z. Wu, "Unmanned aerial vehicle path planning algorithm based on deep reinforcement learning in large-scale and dynamic environments," *IEEE Access*, vol. 9, pp. 24884–24900, 2021.
- [16] Z. Lu, J. Fan, Z. Hou, S. Deng, and F. Jing, "Automatic 3d seam extraction method for welding robot based on monocular structured light," *IEEE Sens. J.*, vol. 21, no. 14, pp. 16359–16370, 2021.
- [17] B. Zhou, R. Zhou, Y. Gan, F. Fang, and Y. Mao, "Multi-robot multi-station cooperative spot welding task allocation based on stepwise optimization: an industrial case study," *Robot. Comput. -Integr. Manuf.*, vol. 73, no. 3, p. 102197, 2022.
- [18] X. Wang, Z. Xia, X. Zhou, Y. Guo, and H. Yan, "Multiobjective path optimization for arc welding robot based on dmoea/d-et algorithm and proxy model," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–3, 2021.
- [19] B. Han, A. A. Ravankar, and T. Emaru, "Mobile robot navigation based on deep reinforcement learning with 2D-LiDAR sensor using stochastic approach," *2021 IEEE International Conference on Intelligence and Safety for Robotics (ISR)*, vol. 22, no. 3, IEEE, 2021, pp. 504–530.
- [20] X. Huang, H. Deng, W. Zhang, R. Song, and Y. Li, "Towards multi-modal perception-based navigation: a deep reinforcement learning method," *IEEE Robot. Autom. Lett.*, vol. 6, no. 3, pp. 4986–4993, 2021.
- [21] T. Qiu and Y. Cheng, "Applications and challenges of deep reinforcement learning in multi-robot path planning," *J. Electron. Res. Appl.: JERA*, vol. 13, no. 4, pp. 101–105, 2021.
- [22] R. Huang, C. Qin, J. L. Li, and X. Lan, "Path planning of mobile robot in unknown dynamic continuous environment using reward-modified deep q-network," *Optim. Control. Appl. Methods*, vol. 58, no. 2, pp. 15–19, 2021.