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OBSTACLE AVOIDANCE PATH PLANNING FOR POWER INSPECTION ROBOTS BASED ON DEEP LEARNING ALGORITHMS

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Abstract. The current research on obstacle avoidance path planning methods for power inspection robots has problems such as poor obstacle avoidance ability and poor inspection effectiveness. Therefore, a planning method for obstacle avoidance path of power inspection robots is proposed. By utilizing motion relationships and the potential field theorem of robot motion, a three-dimensional model of the power inspection robot's route is established to determine the direction of the robot's route when obtaining action tasks. The fuzzy support vector algorithm is used to plan obstacle avoidance paths for the initialized walking path, making the inspection robot intelligent. The experimental results show that the average success rates for avoiding static and dynamic obstacles are 98.37% and 96.12%, respectively. The average time for obstacle avoidance path planning is 1.56 seconds, and it has fast, efficient, and accurate obstacle avoidance and path planning capabilities, which can improve the robot's obstacle avoidance ability and path planning efficiency for dynamic and static obstacles.

Key words: path planning, Inspection robot, three-dimensional model

1. Introduction. Entering the 21st century, with the continuous development of economies and cultures in various countries, the level of technology is also constantly improving. Among them, robotics is one of the most eye-catching development disciplines. The development of robotics has made an important contribution to the progress of social civilization and the development of market economy, and has played an important role in human's food, clothing, housing and transportation. Robots can complete various high-load, difficult, and high-precision tasks that are difficult for humans to complete, such as medical, military, agricultural, and other aspects [1]. This has greatly liberated productivity, improved human labor efficiency, and also improved the efficiency of human technological development, making significant contributions to the technological development of various countries and regions.

Nowadays, automation reform has emerged in many labor-intensive industries. The emergence of automated robots has saved human resources and greatly reduced labor costs. At the same time, labor efficiency in various industries such as manufacturing assembly lines has been greatly improved. Robots have been widely used in many fields, such as medical robots, transportation robots, etc [2]. With the continuous innovation of high-precision sensors and advanced artificial intelligence algorithms, it is not only possible to use robots in large-scale industrial production workshops, but also to complete related tasks in crowded indoor spaces and even within the human body. Some service robots, such as outdoor cleaning robots, robot nurses, and smart home assistants, have greatly improved people's quality of life. The research and development of wheeled inspection robots applied to various industries, such as warehousing and logistics, and electrical equipment inspection work, began as early as the beginning of this century. With the continuous development of modern power systems, both industrial and residential electricity consumption is significantly increasing, and the requirements for the long-term stable operation of substations in the power grid are also constantly increasing [3]. Therefore, how to complete inspection work more efficiently and accurately, the proposal of this issue further promoted the research

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and development process of power inspection robots. In addition, the country has also invested a large amount of financial support in the use of industrial site inspection robots. Currently, China is undergoing a process of developing from traditional manufacturing to modern manufacturing. Revitalizing the manufacturing industry and realizing its industrialization are of great significance for the vigorous development of the economy. In the process of industrial development, mechanical automation is a necessary stage to achieve industrialization. It is not difficult to see from the industrialization development process of developed countries in the past that the improvement of production efficiency and the continuous expansion of industrial productivity must go through the process of mechanization, automation, intelligence, and information transformation [4]. With the rapid development of the national economy, the continuous improvement of industrial production efficiency, and the continuous increase in human resource costs, the use of automated robots instead of manual inspection has gradually become an inevitable direction for industrial equipment inspection and maintenance. The traditional manual inspection method has many shortcomings, such as large workload and low detection efficiency; The detection effect is not satisfactory, and the detection method mainly relies on visual inspection, resulting in significant errors; In some extreme meteorological environments, such as thunderstorm days, traditional manual detection methods pose safety hazards for detection personnel and cannot complete troubleshooting in a timely manner; The traditional inspection method, which mainly involves installing cameras at designated locations, has a large blind spot due to the limitations of the camera's shooting range, making it difficult to truly meet the requirements of comprehensive fault screening within the station. At the same time, due to the cumbersome design of the control system, the large number of equipment installations, and poor economic efficiency, this inspection method has a high false detection rate for faults and poses great difficulties in maintaining monitoring equipment.

2. Literature Review. The increasing amount of data in the power system greatly increases the task of power transmission, and traditional manual power grid inspections face greater risks. Adopting robots instead of manual power grid inspections can not only ensure the health of workers, but also improve inspection efficiency and create higher value economic benefits. The inspection robot must carry out path planning, that is, in an unknown environment with obstacles, plan the best running path that can avoid all obstacles, which is of great significance [5].

Abdallaoui, S conducted a comprehensive and up-to-date overview analysis and rigorous review of the safety and best path of autonomous vehicle. The focus is on sampling algorithms, node based optimization algorithms, mathematical model based algorithms, bioheuristic algorithms including neural network algorithms, and multi fusion based algorithms, which combine different methods to overcome their respective shortcomings. All of these methods consider different conditions and are used in multiple fields [6]. Xu, T proposed an improved artificial potential field method, in which the object can leave the local minimum point trapped by the algorithm while avoiding obstacles and following a shorter feasible path along the repulsive equipotential surface of local optimization. The entire obstacle avoidance process is based on an improved artificial potential field method, which is applied to the path planning action of the robotic arm, along the motion from the starting point to the target point. The simulation results of the research results show that compared with the improved artificial potential field method based on fast exploration random trees, the algorithm proposed in this paper can effectively perceive the shape of obstacles in all selected situations, and can effectively shorten the distance of the planned path by 13%-41%, significantly improving the planning efficiency [7]. Cheng, J proposed an intelligent robot food runner suitable for restaurants with lower prices but better performance. Among them, this article mainly analyzes how to use LiDAR SLAM to establish restaurant maps, positioning, and navigation, as well as how to establish obstacle avoidance and path planning. Through the ROS platform, the entire process of the intelligent robot vegetable runner is simulated and verified, which can meet the needs of restaurants [8].

Traditional power inspection robots, due to their immature technology, may collide with power equipment during the inspection process, resulting in power inspection accidents and causing losses to both the power inspection robots and the power system , therefore, the author proposes a machine learning based obstacle avoidance path planning method for power inspection robots, achieving the goal of safe inspection for inspection robots.

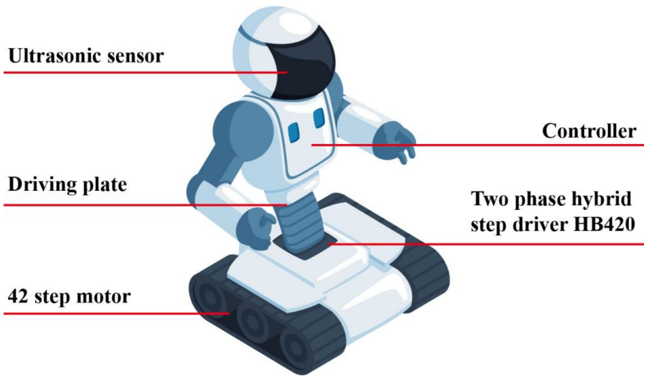


Fig. 3.1: 3D Model of Electric Power Inspection Robot

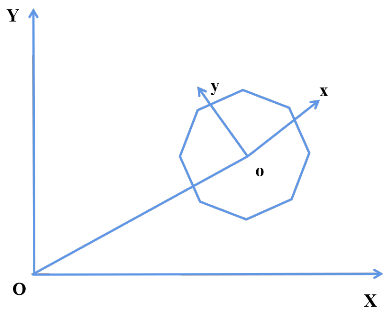


Fig. 3.2: Coordinate System of the 3D Model of the Electric Power Inspection Robot

3. Application of machine learning in obstacle avoidance path planning for power inspection robots.

3.1. Establishment of a three-dimensional model for the route of the power inspection robot . The goal of the author's design of a three-dimensional model for the route of the power inspection robot is to ensure stable inspection, and to enable the power inspection robot to have the ability to recognize and perceive the direction of the inspection path, and to complete the inspection path planning of the inspection task in all aspects [9].

In order to improve the stability of the inspection robot, four intersecting driving wheels are designed at the bottom of the power inspection robot based on physical principles, the motion direction and period of the driving wheels are the same, the specific 3D model of the physical power inspection robot is shown in Figure 3.1.

The perception of direction is very important for power inspection robots. Once the robot's directional perception ability decreases, it will cause the inspection route of the power inspection robot to deviate from the normal inspection route, and may collide with other electronic system inspection obstacles or equipment, resulting in power inspection errors [10]. In order to solve the above problems, the author uses motion models and terrain strength to establish a three-dimensional model of the route of the power inspection robot, so as to optimize the perception angle of the center of gravity of the power robot, therefore, the author chooses the center of mass of the power robot as the center origin of the model, and the two-dimensional coordinate system diagram of the power inspection robot is shown in Figure 3.2.

Simulate the motion behavior of the power inspection machine, firstly, set the direction vector of the four driving wheels of the inspection robot as P, and then combine it with real-time environmental conditions, firstly,

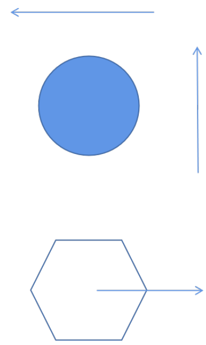


Fig. 3.3: Schematic diagram of the rotation route of the power inspection robot

calculate the relative position of the robot within the inspection range, and the calculation formula is as follows:

$$P_B = |\frac{x(t)}{LW}, \frac{y(t)}{LW}| \sum \frac{1}{L} [\frac{Q}{\prod}] P_n \tag{3.1}$$

Among them, P_B represents the starting position of robot inspection; X (t) represents the directional guidance coefficient of the X-axis of the inspection robot; Y (t) represents the directional guidance coefficient of the Y-axis of the inspection robot; L represents the radius of the driving wheel of the inspection robot; Represents the coordinates of the power inspection robot; Q represents the degree of freedom of the inspection robot during operation; P_n represents the motion direction vector of the driving wheel of the inspection robot. W_x and W_y represent the weight matrices of the X-axis and Y-axis of the 3D model of the power inspection robot route, respectively [11].

The power inspection robot will perform basic inspection behavior operations during the inspection process, such as walking straight, turning, reversing, translating, and rotating, in order to improve the smoothness of the operation of the power inspection robot, the author uses the theorem of resultant force balance to constrain the robot's inspection motion behavior during the robot inspection process. The schematic diagram of the circular motion path planning for the power inspection robot is shown in Figure 3, and the formula is as follows:

$$F = \frac{f_7}{\varepsilon} \sqrt{Fx^2 + Fy^2} \tag{3.2}$$

Among them, f_7 represents the repulsive force of the motion of the electric inspection robot; F represents the combined force of the motion of the electric inspection robot; Fx^2, Fy^2 represents the motion components of the electric inspection robot on the X-axis and axis, respectively; ε represents the robot's motion balance coefficient [12].

3.2. Robot obstacle avoidance path planning. Machine learning technology is widely used in various fields such as home services, industrial guidance, and military operations. Machine learning is divided into two types: Single machine machine learning technology and multi machine machine learning technology, select the best machine learning method based on the difficulty of object-oriented machine learning. The application range of single machine learning technology is relatively limited compared to multi machine machine learning technology, based on the obstacle avoidance path planning method designed by the author for power inspection robots, multi machine machine learning technology is selected, this technology can complete the planning of static and dynamic paths through learning the environment, and has a self verification process during the path planning process to avoid redundant planning paths [13].

The power inspection robot determines its own location and plans the specific path that the power inspection robot needs to inspect based on the inspection tasks sent by the control center. During the planning process, the repulsion function is used to determine the effective range of the inspection, and obstacles within the inspection range are marked using an artificial potential field method. The principle of obstacle marking is that the artificial potential field at the location of the obstacle, combined with the field strength of the real-time environment, will emit a repulsive force outward, which affects the gravitational force of the inspection target on the inspection robot's route. The electric inspection robot determines the specific position of the inspection obstacle based on the magnitude of the gravitational force. The repulsion function is as follows:

$$U_t = \frac{k_1}{O} \tag{3.3}$$

Among them, U_t represents the repulsion function; Indicates the relative distance between the inspection robot and the obstacle; k_1 represents the coefficient [14].

After identifying the effective range and obstacles for inspection, the power inspection robot can complete the planning of obstacle avoidance routes for the first time, this route plan will eliminate the accessible routes with obstacles, but if all routes have obstacles, the obstacle avoidance function of the power inspection robot needs to be activated. The author uses the DWA sliding window method to drive the power inspection robot to avoid obstacles during operation and stably complete the inspection work, the formula for generating obstacle avoidance motion behavior is as follows:

$$y(h) = V_s \times \frac{V_a}{V_b} + \frac{ad_{path} + \beta d_{good} + \gamma d_{obstcle}}{\Delta t} \tag{3.4}$$

Among them, represents the obstacle avoidance command of the power inspection robot; V_b represents the angular velocity of the power inspection robot; V_s represents the linear velocity of the motion of the power inspection robot; V_a represents the acceleration of the motion of the power inspection robot; Δt represents the inspection cycle of the inspection robot; ad_{path} represents the shortest distance between the inspection robot and the obstacle; βd_{good} represents the distance from the endpoint of the trajectory to the local target; $\gamma d_{obstcle}$ represents the maximum obstacle cost for the operation trajectory of the power inspection robot [15].

Using a fuzzy support vector model to set path planning constraints, according to the author's research objectives, setting path planning constraints to maximize the inspection range and minimize the inspection path can improve the efficiency of obstacle avoidance path planning for power inspection robots. The formula for the constraint conditions is as follows:

$$D = \sum_{i=1}^{n} a_i \times \frac{f(k)}{2} + \frac{y(h)}{min_L \frac{c_1+c_2}{2}} \tag{3.5}$$

Among them, D represents the constraint condition model; c_1, c_2 represents the mean of the decision functions for the upper and lower bounds of the fuzzy support vector machine model; a_i represents the membership degree of the fuzzy control algorithm; min_L represents the minimum path for inspection; $f(k)$ represents the kernel function of the inspection probability of the power inspection robot, and the meaning of other unknowns is the same as above. Finally, machine learning technology is used to plan the path constraints and obstacle avoidance behavior instructions for the inspection of the power robot, and the planning formula is as follows:

$$s(t) = f(x, y, z) + \omega \times maxr - Q(x, y, z) \times \mu \tag{3.6}$$

Among them, s (t) represents the inspection path of the power inspection robot; Q (x, y, z) represents the feature vector of inspection behavior classification; μ represents the path planning coefficient; ω represents the inner product of high-dimensional feature space vectors; F (x, y, z) represents the loss function of path optimization.

4. Experimental Results and Analysis. Through the above analysis and design, the design of a machine learning based obstacle avoidance path planning method for power inspection robots has been completed, in order to verify the working performance of this method, the author utilized the obstacle avoidance path planning method for power inspection robots based on GPS navigation technology (traditional method 1) and the obstacle avoidance path planning method for power inspection robots based on carrier free communication technology (traditional method 2) to jointly complete comparative experimental testing, ensuring the scientific nature of the testing [16]. In order to improve the reliability and analyzability of the test results, the inspection

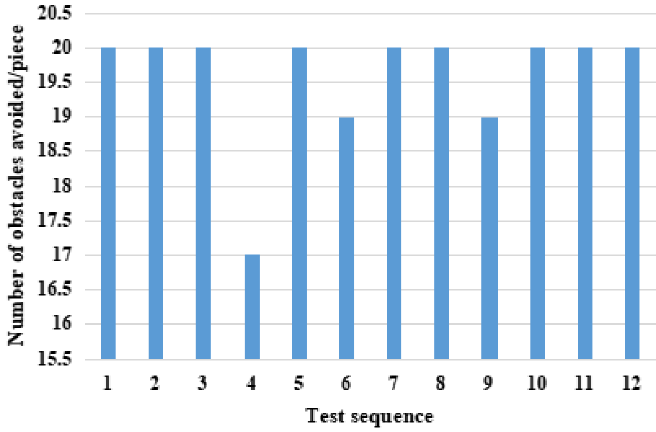


Fig. 4.1: Statistics of Robot Obstacle Avoidance Quantity

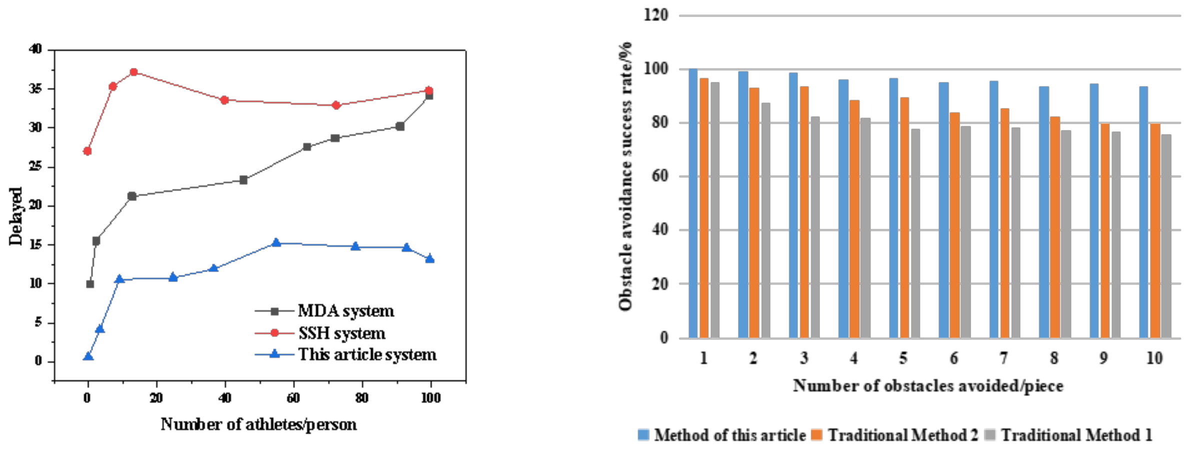
robots tested in the article are all HKD09 series inspection robots, the functions of the drivers, motors, and other accessories of this series of inspection robots are optimal and will not result in the experiment being terminated due to the inspection robot. Set at 12 meters × The 12 meter area is a simulation environment, where 20 rectangular obstacles are unevenly distributed. The starting position and target point coordinates of the inspection robot are [0,0] and [11,11], respectively, with a robot step size of 0.50. 12 repeated obstacle avoidance tests were conducted based on the planned path trajectory, and the obstacle avoidance results are shown in Figure 4.1 [17].

As shown in Figure 4.1, during the obstacle avoidance test of the inspection robot in the established path, among them, the accuracy of obstacle avoidance for 9 times reached 100%, with an average obstacle avoidance rate of 97.92%, proving that the author's method has good obstacle avoidance effect [18].

Comparative experiments were conducted using the author's method to compare the effectiveness of obstacle avoidance with traditional methods 1 and 2, respectively, under the same workspace and number of obstacles, static and dynamic obstacle avoidance experiments were conducted, and the experimental results are shown in Figure 4.2.

From Figure 4.2(a), it can be seen that the author's method outperforms traditional method 1 and traditional method 2 in avoiding static obstacles, in the case of the initial two obstacles, the success rates of obstacle avoidance for the three methods are almost the same, reaching over 99.90%. However, as the number of obstacles increases, the success rates of obstacle avoidance for all three methods show a downward trend, the author's method has an average obstacle avoidance success rate of 98.37% for static obstacles, which is 8.37% and 3.49% higher than the comparison methods of traditional method 1 and traditional method 2, respectively [19]. From Figure 5b, it can be seen that when facing dynamic obstacles, the difference in obstacle avoidance success rates among the three comparison methods gradually widens as the number of obstacles increases. As the number of dynamic obstacles increases, all show significant fluctuations, the author's method has an average obstacle avoidance success rate of 96.12% for dynamic obstacles, which is 15.03% and 9.10% higher than the comparison method of traditional method 1 and traditional method 2, respectively. The results indicate that, the author's method has good obstacle avoidance ability in both static and dynamic obstacles. Under the same conditions, three methods were used to conduct multiple obstacle avoidance path planning experiments for inspection robots, and the data of 8 path planning times is shown in Figure 4.3.

From Figure 4.3, it can be seen that the author's method takes the highest time of 1.80 seconds and the lowest time of 1.40 seconds in obstacle avoidance path planning, with an average time of 1.56 seconds, the traditional method 1 takes the highest time of 3.10 seconds, while the traditional method 2 takes the highest time of 2.10 seconds, with an average time of 1.12 seconds and 0.20 seconds, respectively [20].



(a) Static obstacles (b) Dynamic obstacles

Fig. 4.2: Comparison Test Results for Obstacle Avoidance

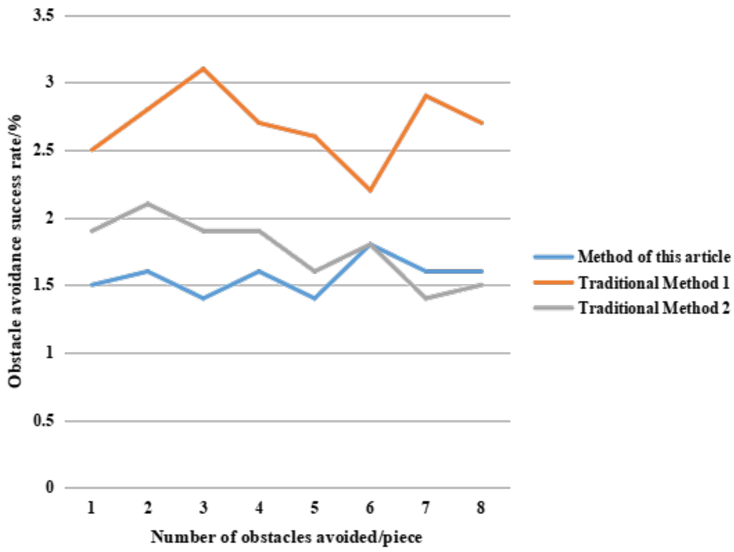


Fig. 4.3: Statistics of robot obstacle avoidance path planning time consumption

5. Conclusion. Based on fuzzy control algorithms, the directional recognition and perception ability of obstacle avoidance paths for power inspection robots has been fundamentally improved, and the robot is controlled to minimize rotation errors during turning behavior. Utilizing motion models and potential field theorems to improve the reasonable path planning ability of inspection robots, resulting in the output of the planned route with minimal obstacle avoidance and the widest effective range of inspection. Machine learning algorithms have improved the self-learning habits and intelligence of power inspection robots for inspection path planning, enabling them to achieve the goal of safe inspection. Obstacle avoidance methods based on machine learning, on the one hand, it can effectively avoid conflicts between algorithm time and accuracy in planning.

On the other hand, by adjusting the repulsive potential function, gravitational potential function, and the calculation of the resultant force, it can enhance the adaptability of the inspection robot to the environment, thereby improving the robot's obstacle avoidance ability and inspection efficiency.

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