Mobile Robot Full Ergodic Path Planning Algorithm for Power Equipment Fault Detection

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Abstract. In order to reduce the abnormal operation of mobile robot caused by collision, a full ergodic path planning algorithm for power equipment fault detection is proposed. Based on the grid method, the workspace of the robot is divided, and the mathematical model of path planning is established. The bb-pso algorithm is introduced to calculate the path. On this basis, the mutation operator is used as the optimization iteration power of the bb-pso algorithm. Therefore, the collision avoidance calculation is carried out to improve the feasibility of the path. The simulation results show that the distance between the path and the obstacles of the proposed algorithm is basically stable between 30-40 cm, and the fluctuation range of the path running time is only 3 min, the average time is 40 min, which has high feasibility.

1. Introduction

In the 21st century, electric power has gone deep into all walks of life, from production, scientific research to the basic life of the broad masses of the people. Without electricity, it will be very difficult to carry out most of the normal activities in social life and people's daily life. Therefore, ensuring the safe supply of electricity plays a vital role in ensuring national social stability. In recent years, the power industry is developing rapidly in the direction of large capacity and ultra-high voltage. To ensure the stable and normal work of power equipment and the safe operation of the whole power system has become the core problem in power management. In order to reduce the heavy task of equipment inspection and the work intensity, improve the detection quality of power equipment, and realize the automation, intelligence and efficiency of power equipment inspection, it is urgent to establish a stable and efficient intelligent inspection system. This paper proposes a mobile robot full ergodic path planning algorithm for power equipment fault detection. The grid method is used to divide the operation range of the robot, and the path planning model is established. The bb-pso algorithm is used to plan the path, and the mutation operator is introduced to update the anti-collision. The simulation results verify the reliability of the proposed method. Through this research, we hope to provide valuable reference for the path planning of mobile robot and help the development of power system detection.
2. Mathematical modeling of path planning based on 1-grid method

2.1. Determining the grid

After the map of robot workspace is obtained, firstly, the obstacles are divided according to their different shapes. The ellipse and irregular figure are calculated according to the smallest rectangle that can be covered, while the convex polygon is triangulated. According to the result of division, the total area of obstacles in the map is calculated\(^3\). Then the size of the grid is determined according to the proportion of the total area of the whole map occupied by obstacles. The calculation method of grid particle size is as follows:

Step 1: Select any obstacle in the map for subdivision and area calculation. For the division of ellipse and irregular figure, we need to find the midpoint of all vertices in the obstacle, and then draw a rectangle with \((x_{\text{max}}, y_{\text{max}})\) and \((x_{\text{min}}, y_{\text{min}})\) as diagonal lines, and calculate the area of the rectangle. The convex polygon is divided into several triangles based on a vertex, and the area of each triangle is calculated. The area of triangle is calculated according to the formula \(s = 0.5ab\sin \alpha\) Calculation, where \(a\) and \(b\) are the length of the side of the triangle with the partition vertex as the vertex respectively, which is the angle between \(a\) and \(b\) of the triangle.

Step 2: Check whether there are obstacles in the map. If there are obstacles, go to step 1 to continue; If not, calculate the total area of the obstacle

\[
S_Z = \sum_{c \in Z} S_c \quad (1)
\]

Where \(Z\) is the set of obstacles in the map.

Step 3: Calculates the grid granularity according to the total area of the map and the total area of the obstacles. \(c_{\text{max}}\) and \(c_{\text{min}}\) are defined as the maximum and minimum side length of the grid respectively, and \(c\) is the final side length of the grid.

2.2. Mathematical modeling of path planning

The set of \(n\) obstacles in the two-dimensional region is \(Z=\{Z_1,Z_2,\ldots,Z_n\}\). Let the starting point of the robot be \(P_0=(x_0,y_0)\), and the position of the target be \(P_e=(x_e,y_e)\). The path \(P\) of the robot is composed of the point sequence \(P=\{P_1,\ldots,P_m,P_e\}\) in the workspace, where \((P_1,P_2,\ldots,P_m)\) represents a path in the global map, that is, a point sequence, and \(P_e\) is a non obstacle point.

On the XOY map, a new \(x'\) axis with \(P_0\) as the origin and \(P_e\) as the end point is established, and the one perpendicular to it is the \(y'\) axis

\[
\begin{bmatrix}
  x' \\
  y'
\end{bmatrix} = \begin{bmatrix}
  \cos \alpha & -\sin \alpha \\
  \sin \alpha & \cos \alpha
\end{bmatrix} \begin{bmatrix}
  x \\
  y
\end{bmatrix} \quad (2)
\]

Where, \(\alpha\) is the angle between \(x\) axis and \(x'\).

The line segment of \(p_0p_e\) is divided vertically by \(m+1\), and \(P_e\) is written as \(P_{m+1}\), where the sequence of intersection points \((P_1,P_2,\ldots,P_m)\) of parallel line cluster \((l_1,l_2,\ldots,l_m)\) perpendicular to \(x'\) and \(y'\) is the sequence of paths. The length LP of the planning path.

\[
L_p = \sum_{i=0}^{m} \sqrt{\left(\frac{L_{P_{i+1}}}{m+1}\right)^2 + (y'_{P_i} - y'_{P_{i+1}})^2} \quad (3)
\]

It can be seen from equation (4) that the path planning problem is transformed into finding the optimal solution in the space of \(y'_{P_i}\) \((i=1,2,\ldots,m)\). The set of \(y'_{P_i}\) \((i=1,2,\ldots,m)\) is taken as the initial particle population of the robot in the process of moving.

3. Robot full ergodic path planning algorithm based on BB-PSO

3.1. Path planning

In order to make the particle swarm optimization algorithm can converge quickly, the topological structure between particles is a fully connected structure. The classical PSO algorithm needs to control
the inertia weight and learning factor to regulate the full ergodic search and local search ability of the algorithm\cite{8}. However, there is no reliable theory to determine the value of learning factor, which depends on experience. In order to overcome this shortcoming, this paper uses the BB-PSO algorithm proposed by Kennedy. In this algorithm, a Gaussian function is used to update the position of particles without setting learning factors and other control parameters. The Gaussian function is determined by the individual optimal and total ergodic optimal of particles. BB-PSO algorithm removes the classical particle position and velocity update formula, and proposes a Gaussian sampling formula based on particle individual optimization and total ergodic optimization to update the particle position.

\[
p_i = \begin{cases} 
    N\left(\frac{p_i + p_{i+1}}{2}\right), & \text{if } U(0,1) < 0.5 \\
    p_i, & \text{otherwise}
\end{cases} 
\]  

When the probability value is less than 0.5, the location update formula of \(p_i\) follows the normal distribution \(U(0,1)\) with expectation of \(\frac{p_i + p_{i+1}}{2}\), and variance of \(|p_i - p_{i+1}|\).

BB-PSO algorithm is applied to full ergodic path planning: the abscissa value of each path node in formula (1) is selected as the decision variable, and the abscissa sequence of all nodes in each path constitutes a particle. Therefore, each hypothetical particle determines a global path\cite{9}. Among them, formula (4) is the fitness function of this paper, namely the path length. Therefore, in the above modeling, the problem of finding sequence \((P_1, P_2, \ldots, p_m)\) to determine the path is transformed into the problem of searching sequence \((P_1, P_2, \ldots, p_m)\). The particle position update process of path planning based on BB-PSO algorithm is shown in Figure 1.

![Fig.1 Path planning process based on BB-PSO algorithm](image)

The end condition of this algorithm is the preset number of iterations, because it is not sure whether the particle has converged or fallen into the local optimum after this iteration, this algorithm can make the algorithm escape from the local optimum through the iteration.
3.2. Iterative optimization

According to the established mathematical model of path planning, particles need to update the reserve set during each update iteration, and update the individual optimal and fully ergodic optimal of each particle from the reserve set. The particles in the reserve set must satisfy two conditions: (1) the fully ergodic path represented by each particle in the reserve set is collision free, that is, all the points on the path are not inside the obstacle. (2) The fully ergodic path represented by each particle in the reserve set conforms to the kinematic constraints of the mobile robot, that is, the path angle change in the fully ergodic coordinate system composed of every three consecutive nodes should meet the kinematic constraints of the current running speed of the mobile robot.

Therefore, in this paper, collision judgment is carried out in the process of particle iteration. According to the robot workspace represented by grid method, for full ergodic path planning, all obstacles on the map are known by the mobile robot. Taking a k-shaped obstacle as an example, let it be stored in variable \( obs \), in which the coordinate ordinal pairs of its \( k \) vertices are stored.

The core idea of whether there is collision in the path determined by each particle is to calculate whether the line formed by any two continuous nodes of the particle intersects with each side of each obstacle. If there is intersection, the particle position is updated by formula (4) several times in the particle position update stage.

In BB-PSO algorithm, under the action of mutation operator, the position of particles in different iteration stages, with different probability, in different degree range to search the new position of particles, can improve the search ability of the algorithm in the full ergodic optimal solution. In this paper, the mutation operator is designed to change with the number of iterations, which can improve the search ability of particles. The mutation operation of particle position is carried out by formula (5) and formula (6).

\[
p_i = \left( \frac{\tau_k}{N_x} \right)
\]

Where: \( p_i \) is mutation operator \((0 < p_i \leq 1)\), \( \tau \) is mutation speed adjustment coefficient, it is a constant \((\tau > 0)\).

\[
\begin{align*}
\sigma &= \left[ \bar{\sigma} - \sigma \right] \cdot p_i \\
\bar{p}_i &= p_i + N(0,1) \cdot \sigma
\end{align*}
\]

Among them, \( \bar{\sigma} \) is the upper bound of the value of the particle decision variable, \( \sigma \) is the lower bound of the value of the particle decision variable. The mutation range of particles in the iterative process gradually expands from local to the whole search space with the mutation operator \( \tau \). When \( 0 < \tau < 1 \), it can accelerate the mutation process and achieve the same mutation probability and mutation range earlier; When \( \tau > 1 \), the mutation process can be slowed down, and the time to reach the same mutation probability and mutation range can be slowed down. In order to achieve the purpose of improving the feasibility of the path.

4. Simulation and analysis

In order to verify the effectiveness of the algorithm, simulation experiments are carried out. At the same time, in order to improve the reliability of the experimental results, the path planning algorithms proposed in literature [5] and literature [6] are used to carry out experiments at the same time.

4.1. Experimental environment

Visual Studio 2010 as the platform, C# language as the programming environment for simulation. The hardware platform is Intel corei5 3.20 GHz CPU; 4GB memory; 500GB hard disk, windows 10 operating system. The parameters are set as follows: the number of population particles is 50, the particle dimension is 20, the maximum speed of particle variable dimension is 10, and the particle
mutation operator is 0.85; The maximum number of iterations is set to 50, and the adjustment coefficient of mutation speed changes from 0.9 to 0.4.

4.2. Experimental results
In the above experimental environment, this paper first compares the distance between the planned path and obstacles under the three methods, and the results are shown in Figure 2.

As can be seen from Figure 2, compared with the three path planning algorithms, the distance between the path and the obstacle is relatively stable, which is basically stable between 30-40cm, within the safe distance range. However, the methods in literature [4] and literature [5] are too large or too small, which is not conducive to the safe operation of the robot. This is mainly because the bb-pso algorithm is used to calculate the path, and the mutation operator is introduced to update and optimize the path, so as to improve its security and effectively avoid collision.

On this basis, the running time of path is compared under different algorithms, and the results are shown in Figure 3.

As can be seen from Figure 3, comparing the three algorithms, the stability of path planning under this algorithm is obviously better than that of literature [5] and literature [6]. In terms of time-consuming change, the maximum change range is less than 3min, and the average time-consuming is basically less than 40min, which has high efficiency. This is mainly because the optimization of the path improves its rationality. In the actual operation process, it can effectively reduce the time cost caused by large angle turning, emergency stop, collision and other factors, and improve the operation efficiency.
5. Concluding
With the continuous development of power system and the popularity of power users, power is more and more deeply into people's daily life, and its role is more and more irreplaceable. To ensure the safe and stable operation of power equipment has become an important and arduous task. Substation is an essential part of the power grid system. With the continuous improvement of the number of substations, the substation is bound to develop in the direction of intelligence and automation. It can be seen that the application of substation inspection robot in substation is a far-reaching measure to realize substation intelligence and automation. Substation inspection robot instead of manual inspection of power equipment, changes the weakness of manual inspection labor intensity and low efficiency, and can transmit data in real time and efficiently, which improves the quality and efficiency of data management system. Path planning is one of the core issues in the research of substation inspection robot, and it is the premise guarantee for the inspection robot to complete the inspection task, safely and accurately from one inspection point to another. Good planning path can make the running route of substation inspection robot short, the time of in place detection fast, save battery energy, and effectively save the verification time between substation equipment operation background and robot equipment.

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