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MULTI-ROBOT PATH OPTIMIZATION AND SIMULATION FOR MULTI-ROUTE INSPECTION IN MANUFACTURING

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Abstract
The research of multiple inspection robots' path simulation planning helps to improve the inspection ability and efficiency of the multi-robot system. This paper studies the problem of cooperative optimization and simulation of multiple robots for multiple inspections in intelligent manufacturing. A dynamic simulation model of the inspection robot is used to construct the state equation of the multi-robot inspection simulation system. The square grid is used to decompose the intelligent manufacturing workshop area and simulate the workshop space. With reinforcement learning, a multi-robot patrol simulation system is created for full coverage path simulation planning. The results show the effectiveness of the system for cooperative optimization control and reasonable path planning.
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Key Words: Intelligent Manufacturing, Multi-Route Inspection, Multi-Robot Cooperation, Patrol Path Optimization, Simulation Modelling

1. INTRODUCTION

With the gradual integration of artificial intelligence and the traditional manufacturing industry, the Internet of Things, cloud computing, and 5G technology have brought considerable economic and social benefits to manufacturing enterprises and promoted the restructuring and upgrading of the industrial source end. The adjustment of industrial structures has also ushered in the rapid development of patrol robots [1-4]. Replacing the manual inspection, which consumes manpower and material resources and has a rough evaluation standard for whether the data operates normally, the inspection robot can not only achieve real-time inspection 24 hours a day but can be more accurate and efficient in data collection and monitoring, greatly improving the efficiency of daily inspection [5-11]. At the same time, the inspection robot can systematically and comprehensively solve the problems of decision-making assistance, management assistance, and implementation supervision by the leadership of manufacturing enterprises from three aspects of decision-making, management, and implementation [12-17].

In the face of distributed problems in production and manufacturing scenarios such as warehouse management and logistics delivery, it is more convenient to apply multi-robot systems. The research on path simulation planning of multiple inspection robots has a positive impact on improving the inspection capability and operation efficiency of the multi-robot system [18-22].

In the complex underground environment, the planned path for the coal mine patrol robot is often too long and not smooth because of low visibility and bad road conditions. To solve these problems, Gao et al. [23] improved the hybrid algorithm of improved artificial fish swarm algorithm (AFSA) and dynamic window algorithm (DWA) for global path planning of coal mine patrol robot and introduced an improved genetic algorithm (GA) to improve the accuracy of path planning. Based on the globally optimal path, a new self-adaptive trajectory evaluation function is designed using the improved DWA, which improves the ability of the patrol robot to avoid local obstacles. In the study of Li et al. [24], the fire risk level of each location to be inspected was obtained through the electrostatic discharge algorithm (ESDA) – non-parallel support vector machine evaluation model is combined with the optimization of the inspection path, and the fire risk level is used to guide the inspection path planning. A discrete ESDA based on ESDA (DESDA) is proposed. Given the shortcomings of long convergence time and proning to fall into the local optimum of DESDA, further improvements are proposed in the form of IDESDA. In the experiment, 11 open calculation examples are used to verify the performance of the algorithm. IDESDA shows higher accuracy and better stability in solving Travelling Salesman Problem (TSP). Multi-robot system has great advantages and wide applications in the fields of ground reconnaissance, environmental monitoring, and key area patrol. However, in the field of multi-robot cooperation, it is difficult to consider both patrol efficiency and path privacy, especially when any intelligent intruder occurs.

Although experts at home and abroad have conducted in-depth research on the path simulation planning method of multiple inspection robots at present, due to the complexity of the layout planning of intelligent manufacturing workshops, the existing methods are often based on the divided workshop space grid for path simulation planning, and it is impossible to obtain the motion path of multiple inspection robots with high flexibility and intelligence.

In particular, if the inspection robots with the same destination have no internal connection, the coordination ability of the intelligent manufacturing multi-route inspection system will be greatly reduced. Given the above challenges, this paper focuses on the collaborative optimization and simulation of a multi-robot path for multi-route inspection in intelligent manufacturing. First of all, the dynamic simulation model of the inspection robot is fully considered in Section 2, and the consistency of the inspection robots' collaborative control simulation is studied based on graph theory, and the state equation of the multi-robot inspection simulation system is constructed. In Section 3, the square grid is used to decompose the intelligent manufacturing workshop area, and then the obtained workshop space grid is simulated and modelled. Through the guidance of reinforcement learning to the simulation of robot actions, a more versatile multi-robot patrol simulation system for full coverage path simulation planning is finally figured out. The experimental results verify the effectiveness of the multi-robot patrol simulation system for multi-robot cooperative optimization control and reasonable path planning.

2. GRAPH THEORY-BASED SIMULATION ANALYSIS OF COOPERATIVE CONTROL OF MULTIPLE PATROL ROBOTS

The multi-robot patrol simulation system can count the historical data of patrol equipment status, and detect the illegal behaviour of personnel, hidden danger data, and other information through data visualization simulation. Through the combination of human-computer interaction and existing business, multi-dimensional data simulation analysis can intuitively and clearly show the production safety status of production enterprises, which is convenient to assist leaders in making accurate decisions, to achieve twice the result with half the effort. The multi-robot patrol simulation system can upload the patrol data in real-time for the personnel to view the patrol track in real-time and realize the real-time report of equipment abnormality and alarm. The management personnel can grasp the front-line business data in real-time and improve the management mode in the work, to realize the standardized, systematic, and intelligent management patrol effect of the management. The multi-robot inspection simulation system has a complete inspection process. The inspection sets time, route, location, standard, processing method, and other detailed definitions and clear instructions. The process is standardized and rigorous so that the inspection is conducted and reviewed according to plans and basis, with certain results. The process is interlinked, effectively and significantly improving the quality and efficiency of the inspection work.

The information coding rules given by the path simulation planning scheme of the general inspection robot can only represent the displacement of the robot in the mathematical sense, but it is not enough to rely on such a simulation planning scheme only to achieve the completion of the inspection task by multiple robots according to the planned optimal displacement path. To accurately model and analyse the stability of the simulation system, this paper fully considers the dynamic simulation model of the inspection robot, studies the consistency of the inspection robot collaborative control simulation based on graph theory, and constructs the state equation of the multi-robot inspection simulation system.

All inspection robots in the intelligent manufacturing workshop area are represented by nodes with marks in the figure, and the communication between any two inspection robots is represented by connecting lines with directions. Assuming that the set of all patrol robot nodes is represented by U, and the edge set of the communication between all patrol robots is represented by O, the representation of the patrol robot communication topology can be represented by $H_P = (U, O)$. For the directed graph, the information communication from the inspection robot i to the inspection robot j is represented by $o(i, j)$, and the information transmission from the inspection robot j to the inspection robot i is represented by $o(j, i)$.

The relationship between multiple inspection machines is characterized based on the matrix theory. The specific required matrices are adjacency matrix X, degree matrix C and Laplace matrix K, in which $X = [x_{ij}]$ is a matrix in the size of $m \times m$. The connection weight value between the inspection machines is represented by the element x_{ij} in the matrix. When there is communication between the patrol robot i and j, let $x_{ij} > 0$, and if there is no communication, let x_{ij} equal to 0.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \ddots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mm} \end{bmatrix} \tag{1}$$

The degree matrix $C = diag\ \{ci\}$ is used to characterize the relationship between adjacent patrol robots, which is the diagonal matrix in the size of $m \times m$. The number of adjacent nodes of each inspection robot is represented by the diagonal elements of C, that is, the sum of the elements of each row of X:

$$C = diag\left(\sum_{j=1}^{m} x_{1j}, \sum_{j=1}^{m} x_{2j}, \cdots, \sum_{j=1}^{m} x_{mj} \right) \tag{2}$$

The Laplace matrix $K = [k_{ij}]$ is a $m \times m$ matrix, which is defined by the following equation:

$$K = C - X \tag{3}$$

i.e.,

$$K = \begin{bmatrix} \sum_{j=1}^{m} x_{1j} & x_{12} & \cdots & x_{1m} \\ x_{21} & \sum_{j=1}^{m} x_{2j} & \cdots & x_{2m} \\ \cdots & \cdots & \ddots & \cdots \\ x_{m1} & x_{m2} & \cdots & \sum_{j=1}^{m} x_{mj} \end{bmatrix} \tag{4}$$

In the multi-robot inspection simulation system, the status of each inspection robot is determined by the status of itself and other inspection robots. Supposing that the status of all robots in the multi-robot patrol simulation system is represented by $a = \{a_1, a_2, ..., a_m\}^T$, the control input of the patrol robot is represented by $v(a) = \{v(a_1), v(a_2), ..., v(a_m)\}^T$, the time is represented by p, and the number of patrol robots in the multi-robot patrol simulation system is represented by m. The following formula gives the state expression of each inspection robot under ideal conditions:

$$\dot{a} = v(a) \tag{5}$$

It is very difficult to build a more accurate system state simulation model in the actual intelligent manufacturing workshop scenario. The item of uncertainty $g(p)$ can be introduced into the simulation model to compensate for the model. That is, $f(t)$ is introduced into the system state simulation model to compensate for the interference of uncertainties in the actual modelling and simulation on the cooperative control of the multi-robot inspection simulation system. Assuming that the current position of the inspection robot is represented by state a, the speed of the inspection robot is represented by $a_i(p)$, and the identity of the inspection robot is represented by i, the first-order state model expression in the actual intelligent manufacturing workshop scenario is given as follows:

$$\dot{a}_i(p) = v_i(p) + g(a_i(p)), i = 1,2,..., m \tag{6}$$

The connection weight between two inspection machines in the adjacency matrix X in graph theory is expressed by x_{ij}. The control law of the multi-robot inspection simulation system for the first-order model is provided by the following formula:

$$v_i(p) = -\sum_{j=1}^{m} x_{ij}\left(a_i - a_j\right), i = 1,2,\ldots,m \tag{7}$$

It is supposed that the displacement, velocity, and acceleration of the inspection robot are determined by $a_i(p)$, $\dot{a}_i(p)$ and $u_i(p)$, and that the nonlinear term in system modelling is expressed by g. The following formula gives a more practical second-order state model expression:

$$\begin{cases} \dot{a}_i(p) = u_i(p) \\ \dot{u}_i(p) = v_i(p) + g(p, a_i(p), u_i(p)) \end{cases}, i = 1,2,\ldots,m \tag{8}$$

From the above formula, it can be seen that the state of the inspection robot in the multi-robot inspection simulation system corresponding to the second-order state model is controlled by acceleration. Assuming that the speed gain of the inspection robot is determined by $\beta \in M+$, and the control law of the multi-robot patrol simulation system for the second-order model is given by the following formula:

$$v_i = -\sum_{j=1}^{m} x_{ij}\left[\left(a_i - a_j\right) + \beta\left(u_i - u_j\right)\right], i = 1,2,\ldots,m \tag{9}$$

3. FULL COVERAGE PATH SIMULATION PLANNING OF MULTIPLE INSPECTION ROBOTS

The path simulation planning algorithm for multiple inspection robots based on task cosine assignment has a good ability to solve the NP-hard problem of combinatorial optimization, but the simulation environment data needs to be obtained in advance in the actual intelligent manufacturing workshop scenario. The algorithm can still have certain adaptability under the condition of a lack of simulation environment information and difficulty in obtaining simulation data manually, which is the key problem to be considered in the innovation of the full coverage path simulation planning method for multiple inspection robots in this paper. In this paper, the square grid is used to decompose the intelligent manufacturing workshop area, and then the obtained workshop space grid is simulated and modelled. Through simulation modelling, the inspection robot is equivalent to the inspection robot with reinforcement learning to perform actions in the workshop space grid. Through the guidance of reinforcement learning to the simulation of robot actions, a more versatile multi-robot patrol simulation system for full coverage path simulation planning is finally figured out.

The A3C network is composed of multiple parallel A2C networks. In the simulation planning model of the full coverage path of multiple inspection robots based on reinforcement learning A3C network, each A2C network is composed of Actor that outputs actions and a Critic network that evaluates the value of actions and guides the next action of the inspection robot. Fig. 1 shows the A3C network structure. In this paper, the advantage function is used to replace the traditional loss function, which can compensate for the large deviation of the strategy gradient and improve the running speed of the model. To fully enhance the effectiveness of the dominance function, this paper uses generalized dominance estimation to optimize the dominance function.

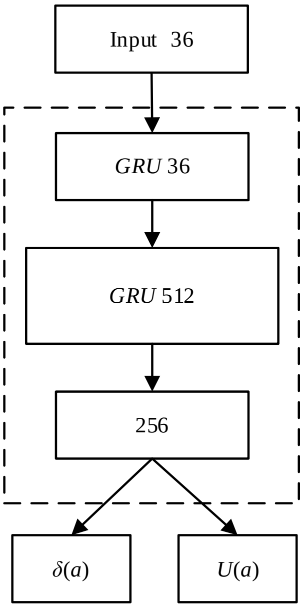

Figure 1: A3C network structure.

In the actual calculation, $\xi^U{}_t = -U(r_p) + s_p + \alpha U(R_{p+1})$ replaces the advantage function, that is, replacing the original advantage function with the advantage function predicted one step forward. If the function predicts l step forward and the forward-looking distance is expressed by k, then:

$$\hat{X}_p^{(l)} = \sum_{k=0}^{l-1} \alpha^k \xi^U_{p+l} = -U(r_p) + s_p + \alpha s_{p+1} + \ldots + \alpha^{l-1} l_{l-1} + \alpha^l U(R_{p+l}) \tag{10}$$

From the above formula, it can be seen that the larger l is, the deviation value of the unbiased estimate of the dominance function $\xi^U{}_t$ is and the greater the variance is. The following formula presents the calculation formula of the generalized dominance estimation:

$$\hat{X}_p^{HXO(\mu,\alpha)} = (1-\mu)\left(\hat{X}_p^{(1)} + \mu \hat{X}_p^{(2)} + \mu^2 \hat{X}_p^{(3)} + \ldots\right) = \sum_{k=0}^{\infty} (\alpha\mu)^k \xi^U_{p+k} \tag{11}$$

It can be seen from the above formula that the calculation process of the above formula is the weighted average of the advantage estimates from the forward-looking one step to the forward-looking infinite step. The smaller μ is, the deviation of the strategy gradient is. When μ increases to 1, the deviation of the strategy gradient is small, but the variance is large. By adjusting α and μ, the variance and deviation of the full coverage path simulation planning strategy gradient are balanced.

When the inspection robot performs simulation movement in the actual intelligent manufacturing workshop scene, each step will make the status of the workshop space grid change greatly, and there are certain potential rules to follow before and after the status change of the workshop space grid. The status information of the workshop space grid with time series characteristics can be used as the input of the reinforcement learning A3C network model in the full coverage problem model of the multiple inspection robots. Before the simulation model predicts the full coverage path of multiple inspection robots, let the workshop space grid state flow circular neural network, fully extract and compress the extracted state sequence characteristics, improve the quality of information obtained by each Actor and Critic network in the A3C network, and finally achieve the goal of reasonably planning the full coverage path of multiple inspection robots.

Based on the full coverage path simulation planning model of multiple inspection robots built in this paper, the status observation data of the inspection robot's workshop space grid is obtained from all the status data of the workshop space grid. Because the status data of the workshop space grid as the input of the simulation model only needs different grid states to be able to distinguish, without other more detailed information, this paper does not need to extract the characteristics of the status data of the workshop space grid but chooses to input the status of the workshop space grid into the simulation model in chronological order through a one-dimensional vector. The value in the input vector changes with each step of the inspection robot and the continuously updated vector input model is propagated forward.

To ensure that the training results of the simulation model converge to the ideal results stably, it is necessary to set up a reasonable reward and punishment function for the full coverage path simulation planning model of multiple inspection robots. To avoid the inspection robot taking up too much weight in completing the full coverage task to obtain rewards during the task execution simulation, in this paper, when the inspection robot enters the uncovered grid or the grid entered by the inspection robot has been covered, the workshop space grid needs to give the inspection robot little rewards, and the reward value is set as 1. Only when there is no uncovered grid in the workshop space grid, the workshop space grid will give the inspection robot 20 rewards. If multiple inspection robots occupy a grid at the same time during the training process, the workshop space grid will give the inspection robot -1 collision penalty. Because each move will produce a movement penalty of -1, the patrol robot will not deliberately wander to obtain more rewards from the grid, thus ensuring that the simulation model has the optimization ability to minimize the total length of the full coverage path of the multiple patrol robots. Fig. 2 shows the structure diagram of the full coverage path simulation planning model for multiple inspection robots.

The parameters of each Actor and Critic network in the A3C network are shared, so the loss function of the model consists of three parts: value loss, strategy loss, and entropy regularization. The value loss is used to characterize the performance of the Critic network, the path simulation planning strategy loss is used to characterize the performance of the Actor network, and the entropy regularization term is used to characterize the quality of the Actor output. Assuming that the predicted value of the Critic network is expressed by $U(r_p)$, the feedback reward of the workshop space grid is expressed by S_p, and the value loss is defined as the distance between $U(r_p)$ and S_p:

$$k_u(p)=\frac{1}{2}\left(U\left(r_p\right)-S_p\right)^2 \tag{12}$$

The loss of path simulation planning strategy is expressed by the following formula:

$$k_\pi(p)=\hat{X}_t^{HXO(\mu,\alpha)}=\sum_{k=0}^{\infty}(\alpha\mu)^k\xi_{p+k}^U \tag{13}$$

It is supposed that the regularization entropy of the patrol robot's action at time p is expressed by $o(p)$, and the weight coefficients of the value loss and entropy regularization terms are respectively expressed by λ_u and λ_o, then the total loss function expression is:

$$k_{total} = \sum_{k=0}^{P} \lambda_u k_u(p) - k_\pi - \lambda_o o(p) \tag{14}$$

The full coverage path simulation planning model of multiple inspection robots combined with action space learning combines the action space of multiple inspection robots into a one-dimensional vector and sets the optimization goal of reinforcement learning as the full coverage of the workshop space grid and the shortest number of movement of the inspection robot.

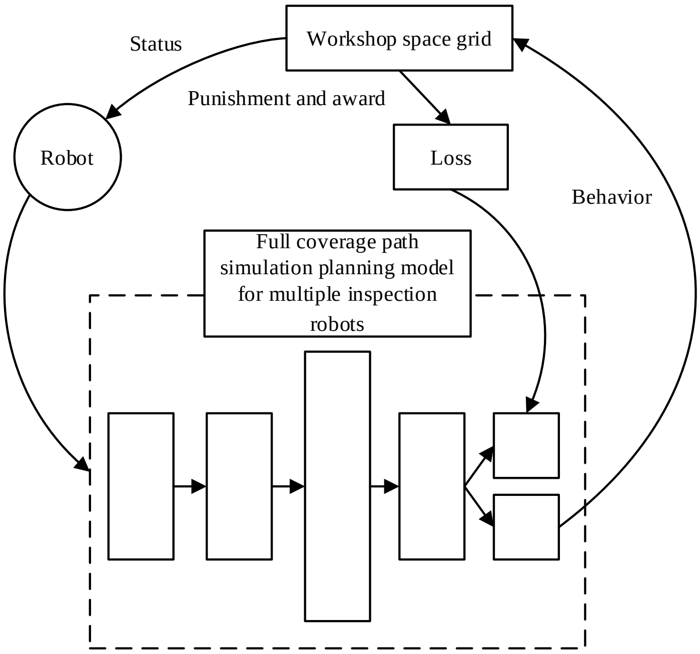

Figure 2: Structure of full coverage path simulation planning model for multiple inspection robots.

4. EXPERIMENTAL RESULTS AND ANALYSIS

Before using the simulation model built in this paper for simulation, this paper first divides the intelligent manufacturing workshop area map environment into two-dimensional grids. Fig. 3 shows the simulation planning results of the inspection path of three inspection robots in a dynamic environment. It can be seen from the figure that there are three types of static areas in this map environment: production equipment distribution area or staff rest area. By default, the travel status of the patrol robot outside these three static areas is straight and has a free travel direction. At the beginning of the simulation experiment, the step length, start grid point, and end grid point of each inspection robot are set. In the given grid area of workshop space, the red line, blue line, and yellow line are the patrol paths of robots PR1, PR2, and PR3 respectively. It can be seen from the figure that the cooperative control strategy proposed in this paper successfully solves the problem of patrol path simulation planning for multiple robots. Fig. 4 shows the consistency of the status of multiple inspection robots in the process of path simulation planning. The horizontal and vertical coordinates of the curve in the figure are the position coordinates of the inspection robots in the workshop space grid area. It can be seen more clearly that the running track target of each inspection robot has been achieved, and the time to reach the target position is consistent.

Table I shows the basic data table of multi-robot patrol inspection. It can be seen from Table I that PR1 has a higher priority than PR2 and PR3 in patrol path planning. Its patrol process is in the state of being given way by PR2 and PR3, and the total patrol path length has not changed significantly before and after the conflict with PR2 and PR3. When the patrol paths of PR2 and PR1 conflict, PR2 pauses at the current grid point and actively evades other robots and static areas in the subsequent patrol process, so its patrol time increases. When there is a conflict between the inspection path of PR3 and PR1, PR3 will carry out local secondary planning of the inspection path, and its inspection path length and inspection time will also increase. It can be seen from the experimental results that when PR1, PR2, and PR3 reach the target position at the same time, that is, when the state consistency in Fig. 4 is met, the simulation model takes the most appropriate time and successfully solves the path conflict problem.

Table I: Basic data sheet of multi-robot patrol inspection.

Robot Code	Start grid point	Target grid point	Pause waiting for the step	Initial route	Actual route
PR1	1	82	0	27.458	27.458
PR2	13	63	1	21.089	21.923
PR3	22	49	0	25.466	26.253

Table II: Number of patrol robots reaching the target position.

Model	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	Experiment 6	Experiment 7	Experiment 8
GDE3	4	5	6	7	8	9	7*	10
NSGAII	4	5	6	7	8	9	10	5*
PRIMAL	4	5	6	7	8	9	8*	9*
IL-GNN	4	5	6	7	8	9	10	10*
G2RL	4	5	6	7	8	9	9*	11
Model in this paper	4	5	6	7	8	9	10	11

Table III: Time steps to reach the target location.

Model	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	Experiment 6	Experiment 7	Experiment 8
GDE3	127	134	142	161	159	173	187*	194
NSGAII	130	134	141	159	158	176	182	173*
PRIMAL	131	137	143	156	162	175	171*	173*
IL-GNN	127	132	141	147	170	168	171	175*
G2RL	128	129	143	143	165	175	172*	190
Model in this paper	120	125	124	125	128	127	126	130

Further, this paper increases the number of inspection robots to 8 and continues to verify the effectiveness of the simulation planning model for the full coverage path of multiple inspection robots. Table II shows the statistical results of the number of patrol robots reaching the target location. Table III shows the time steps to reach the target location. Data that does not meet the requirements of the path coordination optimization experiment is marked with "*". It can be seen from the table that GDE3, NSGAII, PRIMAL, IL-GNN, G2RL, and other models involved in the comparison have not reached the end grid point with the increase of the number of patrol robots, but this is not the case in the model of this paper. The time steps used in PRIMAL, GDE3, NSGAII, IL-GNN, and G2RL models have an obvious trend of increasing with the number of patrol robots. However, the time-step growth trend of this model is not obvious, which verifies the effectiveness of this model. Fig. 5 shows the growth trend of time step with the number of inspection robots, which further verifies the above results.

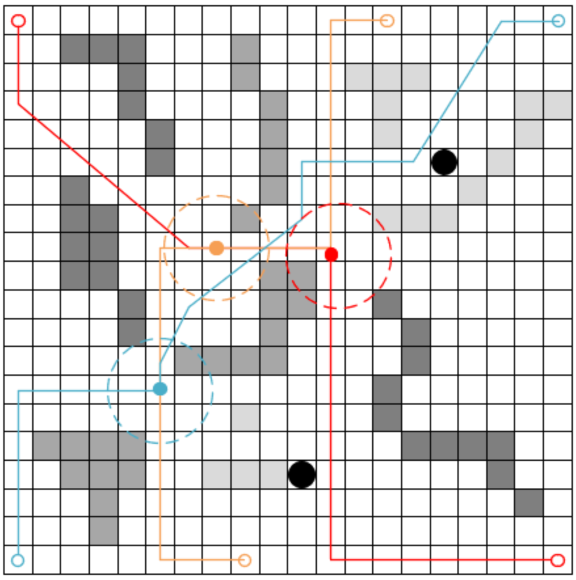

Figure 3: Simulation planning of inspection path of inspection robot in a dynamic environment.

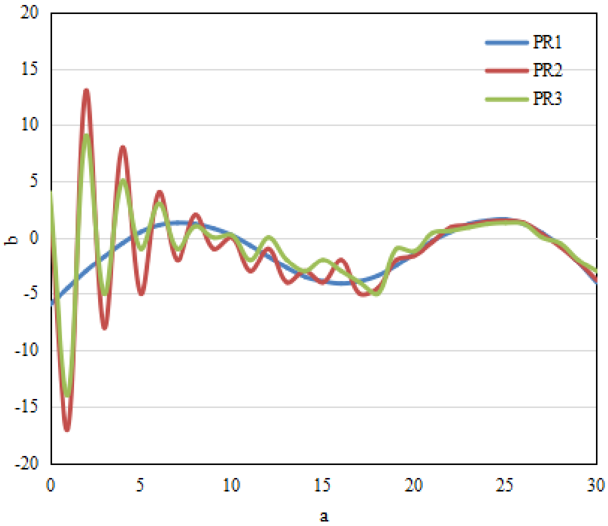

Figure 4: State consistency of multiple patrol robots.

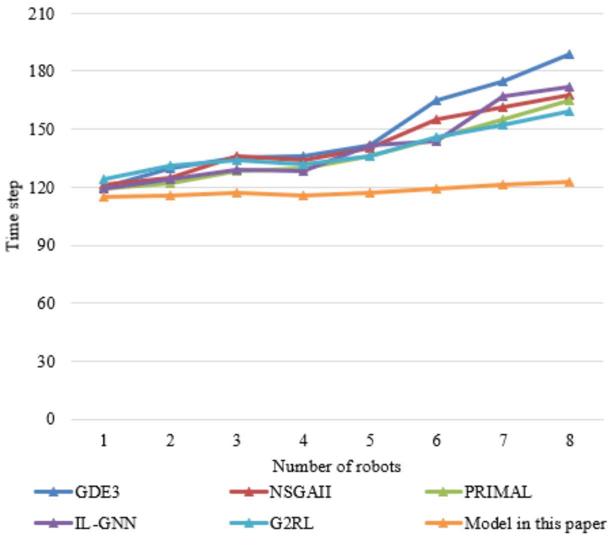

Figure 5: Trend chart of time step increasing with the number of patrol robots.

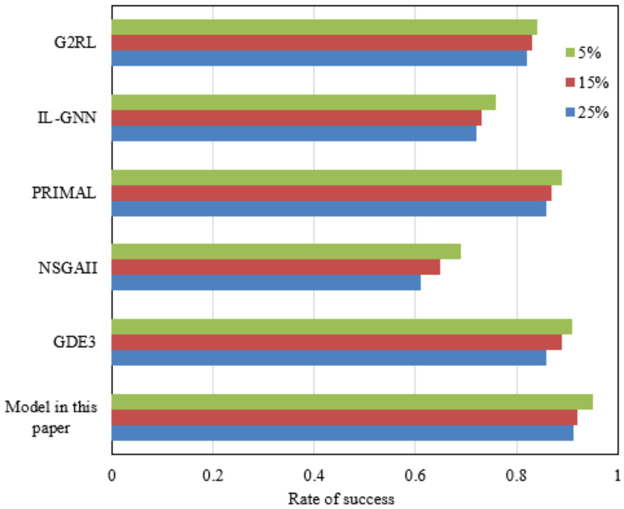

Figure 6: Visualization of the results of different models on the success rate of path planning.

To better compare the path planning performance of different models, the path planning success rate of different models is visualized, and the results are shown in Fig. 6. It can be seen from the figure that when the static area density is low, the path planning success rate of the model in this paper is not largely different from that of the models participating in the comparison. With the increase of static area density, the path planning success rate of other models shows a slight downward trend, but the path planning success rate of this model does not have a significant decline. In addition, with the increasing number of patrol robots and the density of static areas, it can be found that the path planning success rate of other models participating in the comparison has a significant downward trend. In contrast, the path planning success rate of this model has declined more slowly.

5. CONCLUSION

In this paper, the problem of path cooperative optimization and simulation of multiple robots for intelligent manufacturing multiple inspections is studied. First, the dynamic simulation model of the inspection robot is fully considered, the consistency of the inspection robot collaborative control simulation is studied based on graph theory, and the state equation of the multi-robot inspection simulation system is constructed. The square grid is used to decompose the intelligent manufacturing workshop area, and then the obtained workshop space grid is simulated and modelled. Through the guidance of reinforcement learning to the simulation of robot actions, a more versatile multi-robot patrol simulation system for full coverage path simulation planning is finally figured out.

The simulation planning results of three patrol robots in a dynamic environment are given, and the consistency of the state of multiple patrol robots in the path simulation planning process is shown. The basic data of multi-robot inspection is given, and it is verified that when the state consistency is satisfied, the simulation model takes the most appropriate time and successfully solves the path conflict problem. The number of additional inspection robots is increased to 8, and the time steps to reach the target position are given, which verifies the effectiveness of the multi-robot inspection simulation system for multi-robot cooperative optimization control and reasonable path planning. Finally, the results of different models in the path planning success rate are visualized, and the path planning success rate change curves of different models under different static area densities are given, which verifies that the model in this paper always maintains a high path planning success rate performance compared with other models participating in the comparison.

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