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Research on Robot Task Matching Mechanism based on Improved Genetic Algorithm

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Abstract

With the continuous progress of the Internet technology, the logistics industry is also booming, and at the same time, higher requirements have been put forward for the management of warehousing, and in recent years, intelligent robots have been put into use in the warehousing system, and the use of robots not only prevents personnel from being injured, but also saves costs. To address the problem of uneven task allocation of robots in the warehouse environment, and also to avoid the conflict of mobile robots in the execution of the task, an improved genetic algorithm is proposed to solve the problem of task allocation of warehouse robots, which optimises the task allocation scheme of intelligent mobile robots and improves the task completion efficiency. Genetic algorithm, as an intelligent optimisation algorithm simulating natural evolution, has global search capability and parallel processing capability, and has better robustness in solving the nonlinearisation of load, so it is widely used in solving the robotic task allocation, with the task load and path in the task allocation of intelligent mobile robot as the optimisation objective, the genetic algorithm adopts "Elite The genetic algorithm adopts the composite selection operator of "elite + threshold + tournament", and the simulation test is carried out on MATLAB, after comparing with the basic genetic algorithm, this algorithm improves the efficiency of the storage system and allocates reasonable robot loads, and this algorithm is more effective in the optimal scheme of robot task allocation.

Keywords

Genetic Algorithms; Robots; Task Allocation; Selection Operators.

1. Introduction

With the rapid development of e-commerce and the continuous proliferation of order tasks, robots need to respond to multiple orders at high speed, the traditional single-robot single-task allocation can no longer meet the current needs of multi-robot multi-task allocation will become the mainstream[1]. The task allocation of warehouse robots is actually a combinatorial optimisation problem, which is the MTSP problem in optimisation theory. Solving the optimisation problem inevitably appears in how to deal with the relationship priority between tasks. For such problems, for this reason, Deng Fuqin[2] proposed a multi-robot task allocation algorithm combining genetic algorithm and rolling scheduling, this method produces individuals that are not prone to violating constraints, which improves the efficiency of warehousing, but the practicality is not ideal.Li Qinyuan, for the scalability of the task allocation, regarded the allocation of the task as a game [3], and proposed a CF algorithm, which improves the effective allocation of solution quality, but inevitably falls into

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local optimum. The problem of collision can not be avoided during the operation of the robot, in order to reduce such problems, literature [4] introduces a collision penalty term and proposes a genetic algorithm with collision detection. Yanli Guo proposed an allocation method with sexual and asexual hybrid genetic algorithms for collaborative planning of multiple robots with multiple workstations, which achieves joint optimisation of meta-heuristic nested multi-robot task allocation and single-robot path planning [5]. However, the task load degree of robots is rarely mentioned in the literature, for this problem, considering the impact of task load on task allocation, and also to shorten the work cycle, genetic algorithms are used to solve it, and genetic algorithms are widely used in multi-objective optimisation problems[6]. However, the traditional genetic optimisation algorithm, there are shortcomings, such as easy to fall into the local optimum, for this reason, the article will use the composite selection operator to avoid this problem, and to improve its ability to select the best.

2. Problem Modelling

2.1 Problem Description

Warehouse robot efficiency affects the efficiency of the entire warehousing system, the general warehousing robot is responsible for picking, handling, etc. With the continuous development of science and technology, warehousing robots are also constantly being developed and improved. Here we take intelligent service robots and three-dimensional warehouse as an example, intelligent service robots docking new generation of service robot development strategic planning and artificial intelligence technology development direction, the same three-dimensional warehouse in the storage environment is one of the very important links. As in Fig. 1.

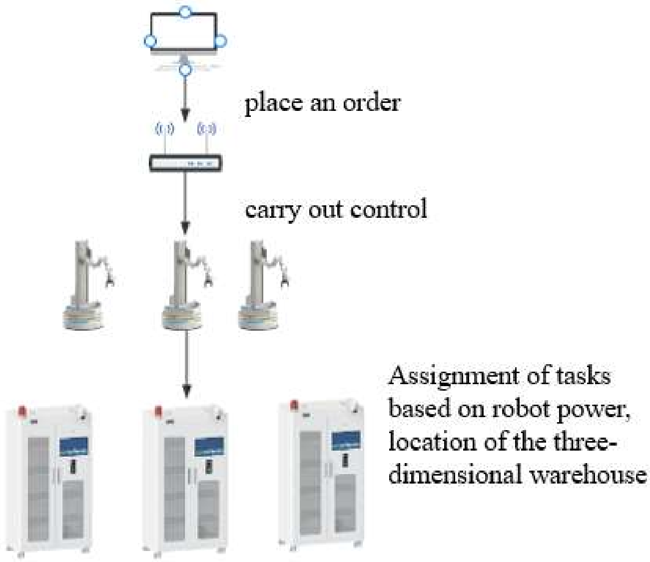

Fig. 1 workflow chart

An order is placed by the customer through the intelligent warehousing system, and then the task is assigned by an algorithm, and the pc controls the corresponding robot through the order, arrives at the corresponding three-dimensional warehouse, and completes the task gripping.

The task allocation of multi-robot multi-warehouse in a warehousing environment is similar to the multi-traveller problem (MTSP), which is a classical NP-hard problem. Assume that there are N warehouse handling tasks and M robots, and m ($m \leq M$) robots are dispatched to perform the tasks in their "free" robot set D_s,with one and only one robot traversing each task point except the departure point.

For this we assume the following premises:

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(1) The robots have sufficient power;

(2) Each robot has the same speed;

(3) Each robot takes the same time to complete each task;

(4) Each robot has the same structure and parameters.

2.2 Problem Modelling

The set of robots $D_s = \{R_1, R_2, R_3 \ldots R_k \ldots R_m\}$ " Assign robot R_k to the tasks of warehouse handling for n $\{A_1, A_2, A_3 \ldots A_i \ldots A_n\}$ $(n \leq N)$ warehouse handling tasks, and robot R_k traverses the n grasping tasks from the starting point A_1 and returns to the initial point.

Define the variables:

$$T_{ij}^{k} = \begin{cases} 1 \text{ for robot } R_k \text{ from } A_i \text{ to } A_j. \\ 0 \text{ means the robot didn't go from } A_i \text{ to } A_j. \end{cases}$$

B_{ij} denotes the distance from task point A_i to task point A_j and B_R is the robot length. This leads to the formula for the sum of all distances travelled by the robot R_k over the assigned task:

$$C_k = \sum_{i=1}^{n} \sum_{j=1}^{n} B_{ij} T_{ij}^{k} - B_R \qquad k=1,2,3,\ldots m \tag{1}$$

Collaboration between robots is an important indicator for task allocation, and task load is added as an indicator to guarantee the reasonableness of task load between robots.

$$Z = \sqrt{\sum_{i=1}^{m} \left(\sum_{k=1}^{n} t_i^k - \frac{1}{m} \sum_{i=1}^{m} \sum_{k=1}^{n} t_i^k \right)^2 \frac{1}{m}} \tag{2}$$

$$t_i^k = \begin{cases} 1 \text{ indicates that robot } R_k \text{ has arrived at } A_i \text{ and completed its mission.} \\ 0 \text{ means that robot } R_k \text{ has not passed through } A_i. \end{cases}$$

A smaller Z indicates a smaller difference in task load between individual robots. Next the objective function can be expressed as:

$$F = Z + C \tag{3}$$

$$C = \sum_{i=0}^{k} C_k \ (0 \leq k \leq m)$$

$$\sum_{k=1}^{m} t_i^k = \begin{cases} m & i=0 \\ 1 & i=1,\ 2,\ 3,\ \ldots,\ n \end{cases} \tag{4}$$

$$\sum_{i=0}^{n} T_{ij}^{k} = t_i^k,\ (\forall j=0,1,2\ldots n; k=1,2\ldots,m) \tag{5}$$

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$$\sum_{j=0}^{n} T_{ij}^{k} = t_i^k, (\forall i=0,1,2,\ldots n; k=1,2,\ldots,m) \quad (6)$$

$$h_{max} \geq \sum_{i=1}^{m} t_i^k \geq h_{min} \quad (7)$$

Equation 4 indicates that the robot R_k starts from the starting point A_0, and except for point A_0, all the other mission points are strictly visited once. Equation 5 indicates that there can only be one entry point connected to the exit point, here for the convenience of calculation, assuming that the warehouse exit point and entry point are in the same location, from point A_1 to enter the warehouse is still A_1 to go out of the warehouse in the end.

Formula 6 indicates that there can only be one entry point and one exit point connected to the warehouse. Equation 7 indicates that the tasks assigned to robots R_k must be between the minimum number of tasks and the maximum number of tasks.

3. Genetic Algorithm

3.1 Coding Strategy

The solution using genetic algorithm requires encoding of chromosomes and the encoding method determines the performance of the algorithm. Here the breakpoint marking method is used for encoding.

(1) Firstly, the set representing the number of task points is labelled as 1, 2,...,n and m breakpoints are added using negative integers for numbering, with -1, -2,...,-m denoting the m breakpoints.

(2) Combine 1, 2,...,n with -1, -2,...,-m to form a gene sequence with breakpoints separating the sequences.

3.2 Initialisation of the Population

The initialisation of the population represents the mapping of the information in the solution space, the wider the coverage of the initial population, the greater the probability of containing the global optimal solution, so the initial population will determine the solution performance of the genetic algorithm to a certain extent[7].

3.3 Adaptation Function

The objective function is mapped to the fitness function, and the fitness is calculated from the fitness function, and the size of its value indicates how well the corresponding individual adapts to the environment. The larger its value is, the better it is.

$$f=\frac{1}{Z+C} \quad (8)$$

3.4 Selection Operator

In the population in accordance with a specific probability to select the more excellent individuals, will be selected individuals will be used as the parent generation to cultivate and reproduce the offspring, when the adaptation of the individual, the higher the chances of being selected as the parent generation, and its excellent genes will be inherited with it. Generally there are three common selection algorithms which are roulette algorithm, tournament method and best individual retention strategy [8].

Elite strategy is a method that ensures that the most adapted members of the population are directly transitioned to the next generation. Generally the population capacity is not very large and the two most adapted members are selected and copied directly to the next generation without crossover and mutation. The optimal individuals that emerge in this way will not be destroyed by crossover and mutation operations, and each individual in the resulting population will not be worse off than an individual in the previous generation, and should generally be used in conjunction with other selection methods. For example, gambling wheel selection method or tournament selection.

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Tournament selection algorithm: This algorithm removes a certain number of individuals from a population several times and then selects the genetically optimal one of them to enter the next generation of the population. This operation is repeated several times until the size of the offspring population reaches the original specified population size. The specific operation steps are as follows:

(1) Determine the number of selected individuals.

(2) Randomly select the number of individuals from the population to enter the next generation, calculate their fitness values, and repeat this operation until the population size reaches the original specified population size if the fitness value is large, indicating that the genes are good.

(3) Repeat step (2) several times until a new population size is formed.

The "elite strategy + threshold + tournament" composite selection algorithm is adopted. First of all, according to the adaptation degree from high to low to sort, design a threshold, such as 10%, the first 10% according to the elite strategy, directly into the next generation, the remaining all the groups, according to the tournament selection method, through the crossover and mutation into the next generation. This gives the algorithm better convergence and optimality seeking ability.

3.5 Crossover and Variation

In genetic algorithm crossover operator is used as the main operator because it has global search ability, while the variation factor is used as a secondary because it has local search ability[9]. The combination of crossover and mutation can achieve both global and local search ability, the task assignment of the robot is coded using integer pairs of cities, and after determining the crossover probabilityp_c $(0<p_c<1)$, the crossover operation is performed according to the crossover probability p_c.[10].

Mutation is similar to genetic mutation in biology, and the probability of performing a mutation operation is called the mutation operator. Generally the mutation operation is performed on them according to the mutation probability p_m $(0<p_m<1)$ using reciprocal mutation.

Two genes are randomly selected in the chromosome for position swapping. As in Fig. 2:

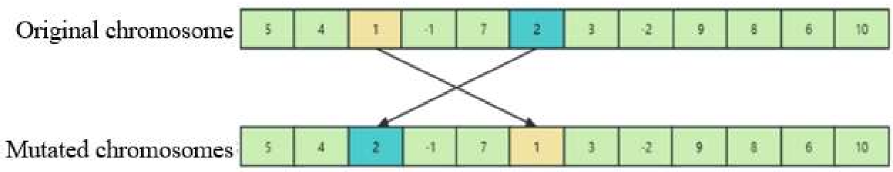

Fig. 2 Swap variation

Table 1. Pseudocode

```
Input: coordinates of each mission point
Output: results of tasking
1. Generate task points by coordinates.
2. Determine parameters such as thresholds, variation rates, crossover rates, etc.
3.While i< Number of iterations
   Coding of individuals
   Calculate the fitness of the individuals
    Sort individuals according to fitness Take all individuals at threshold* and direct them to the next generation
   Generate new population using roulette wheel selection method population_new
   Generate offspring using cross-evolution
    Mutate individuals to get population, elite strategy to get population, combine to population
   Record and save the current optimal result min_info
End
```

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4. Algorithm Simulation

The platform on which the algorithm runs is 64-bit Windows 10, Intel Core i5-9300H CPU (2.40 GHz), 16 GB RAM, and the algorithm compiler is MATLAB 2014a.

Table 2. Parameter Settings

Lower limit of tasking for one robot	Maximum number of tasks assigned to one robot	Task point	Number of robots	population
4	9	35	5	10

Simulation experiment: firstly, 35 task points are generated by inputting the coordinate points.

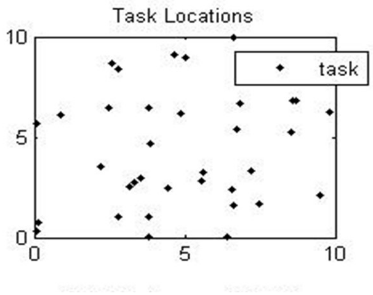

Fig.3 Task

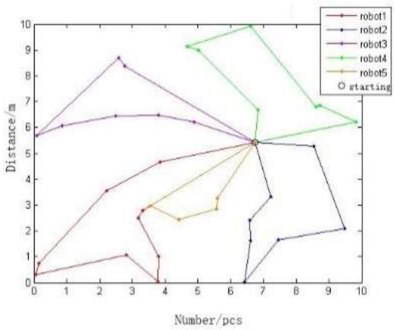

Fig.4 Traditional algorithm

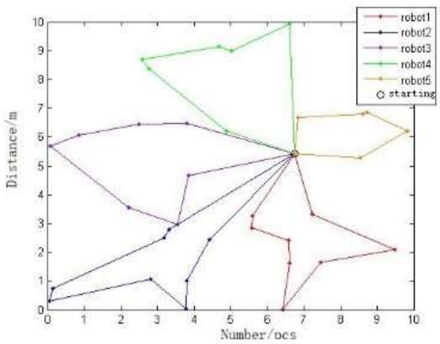

Fig.5 Original algorithm

Algorithm Comparison:

Table 3. Comparison of assigned tasks

Robot	Traditional algorithm	Original algorithm	Number of tasks assigned to the genetic algorithm	Number of tasks divided by this algorithm
R_1	A_{18},A_{10},A_2,A_1,A_4,A_3,A_5,A_{16},A_{17}	A_{34},A_{35},A_{31},A_{32},A_8,A_{33},A_9,A_{30}	9	8
R_2	A_{30},A_{31},A_{32},A_8,A_{33},A_9,A_{29}	A_{16},A_{17},A_2,A_1,A_4,A_3,A_5,A_{14}	7	8
R_3	A_{20},A_{19},A_{13},A_7,A_6,A_{11},A_{12}	A_{19},A_{13},A_7,A_6,A_{10},A_{15},A_{18}	7	7
R_4	A_{26},A_{22},A_{21},A_{23},A_{24},A_{25},A_{28}	A_{20},A_{12},A_{11},A_{21},A_{22},A_{23}	7	6
R_5	A_{15},A_{14},A_{34},A_{35}	A_{26},A_{24},A_{25},A_{28},A_{29}	4	5

Table 4. Comparison of algorithms

Algorithm type	Number of robots reaching mission ceiling(number)	Number of robots reaching the lower limit of the task (number)	Distance (m)
Genetic algorithm	1	1	75.4664
The algorithms in this paper	0	0	72.4525

In the actual warehousing context of multi-task staggered coexistence and security elements, it is important to determine the sequence of tasks to be carried out, from the above analysis, the task points assigned by this algorithm are more balanced than those assigned by the traditional algorithm, the tasks assigned by this algorithm do not reach the upper limit and lower limit of the robot's criteria, and the distance moved by the robot is 3.0139m less than that of the traditional algorithm, in general, this algorithm is more suitable for warehousing robot task assignment. Overall, this algorithm is more suitable for task allocation of warehouse robots.

5. Conclusion

This study focuses on solving the problem of task allocation of warehouse robots by genetic algorithm, designing and adding the task load degree for the load balancing problem in task allocation, and solving the genetic algorithm by using the composite selection operator. The results indicate that the tasks assigned by this algorithm are more balanced than the traditional algorithm, and the distance moved by the robot is shorter than the distance moved by the traditional algorithm by 3.0139m, which is more efficient, and the design of the proposed task allocation algorithm is confirmed to be feasible and practical by simulation examples.

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