Research on Multi-robot Coordination Planning Based on Artificial Immune Algorithm and Convolutional Neural Network

Xiaodong Zhang, Tao Di *

Department of Mechanical and Electrical Engineering, Lanzhou Vocational Technical College, China
* Corresponding author: Tao Di

Abstract: The operation control mechanism of multi-robot system integrates intelligent control theory, artificial life theory, evolutionary algorithm and robot programming technology, etc. It is a research topic in the field of robotics and artificial intelligence that has attracted much attention. The use of the combination of evolutionary algorithms and artificial life theory to study the simulation and design optimization of multi-robot collaboration problems is an important development direction for the research of multi-mobile robot systems. This paper introduces the overall research status and basic theory of multi-robot systems at home and abroad, and designs and studies the neural network behavior decision-making system based on immune genetic algorithm. It is proved that the neural network behavior decision-making system optimized by immune genetic algorithm has good decision-making ability during the whole handling period.

Keywords: swarm robots; immune genetic algorithm with elite retention; artificial neural network; multi-robot collaboration

1. Introduction

The multi-robot system participates in collaborative tasks as a whole, not simply merging multiple robots together. Simply stacking multiple robots together will not only fail to complete the task with higher performance, but may lead to conflicts and confrontations between multiple robots, thereby reducing the overall performance of the system. In fact, in this society composed of multi-robot systems, because each robot has a certain degree of autonomy, it can plan its own path and behavior according to the state of the surrounding environment according to the information and rule library in its own information database and even learn rules. , Status, and when multiple robots collaborate to complete tasks, in order to reflect collaboration and achieve the purpose of collaboration, it is necessary to exchange a large amount of information between individuals, and it is necessary to negotiate to resolve conflicts and confrontations generated during their respective planning, so multiple robots should form In an autonomous collaborative system, in addition to formulating the autonomous planning of each robot, it also analyzes the possible conflicts based on the goals of the collaborative task, formulates collaboration strategies, and combines the autonomy and collaboration of each robot.

The cooperation of multi-robots includes two aspects: one is multi-robot coordination, and the other is multi-robot collaboration. When a multi-robot system is given a task, the first problem it faces is how to organize the robots to complete the task. At this time, the problem to be solved is how to cooperate effectively between the multi-robots. When the respective tasks and relationships are determined through a certain mechanism, the problem becomes how to keep the movement coordination between robots, that is, multi-robot coordination. Multi-robot collaboration and multi-robot coordination are two different and related concepts in the research of multi-robot systems. Multi-robot collaboration mainly studies high-level organization and operation mechanism. The focus of multi-robot coordination research is the specific motion control problems after the cooperation relationship between robots is determined.

2. Basic Theories and Methods of Multi-Robot System Research

We apply artificial life and evolutionary algorithms to the design and research of multi-robot systems. Among them, the artificial neural network can continuously adapt to the changes of the external environment through its self-organization and self-learning, and it is easy to model by computer. The artificial immune algorithm is a bionic optimization algorithm proposed based on the mechanism of the natural immune system. It has obtained continuous inspiration from the many excellent characteristics of the natural immune system. It has created and invented numerous immune systems, models and methods to solve complex problems. Engineering issues and social issues.

2.1. Artificial Neural Network Theory

Artificial neural network is a computational model that abstracts, simplifies and simulates the neural structure of the brain, also known as a parallel distributed processing model. It is composed of a large number of information processing units with simple functions and self-adaptive capabilities—artificial neurons connected by a certain topology in a massively parallel manner. Neurons are the abstraction, simplification and simulation of the functions of human brain nerve cells. A single neuron is forward-looking, and its basic structure is shown in Figure 1.It is a non-linear information processing unit with multiple inputs and multiple outputs.

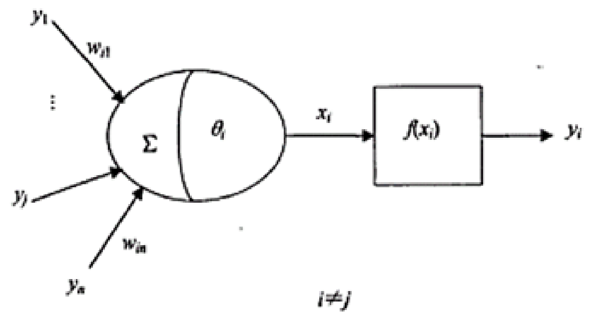


Figure 1. Neural network neuron model

The y_i is the output of neuron i, which can be connected with multiple other neurons through connection weights, y_i is the output of neuron j connected to neuron i, and is also the input of i, and $i \neq j(j = 1,2, \ldots, n), w_{ij}$ is the connection weight of neuron j to i; The θ_i is the threshold of neuron i; $f(x_i)$ is a non-linear function. The output of neuron i can be described by the following formula:

Set $$y_i = f\left(\sum_{j=1}^{n} w_{ij} y_j - \theta_i\right), i \neq j \quad (1)$$

Then $$x_i = \sum_{j=1}^{n} w_{ij} y_j - \theta_i$$

$$y_i = f(x_i) \quad (2)$$

2.2. Artificial Immune Algorithm

One of the results of applying the mechanism of natural immune system to optimization calculation is artificial immune algorithm, which is based on genetic algorithm and can effectively overcome the shortcomings of insufficient group diversity maintenance ability and easy to fall into local optimum. The difference with is the group renewal strategy, which only replicates based on the fitness of the individual, and replicates based on the fitness and concentration of the individual, so it has a strong ability to maintain diversity. Artificial immune systems have also been widely used in knowledge discovery and data mining, robot control, fraud detection and other fields.

Immune algorithms can be roughly classified into group-based immune algorithms and network-based immune algorithms. There is no direct connection between the elements in the system formed by the former. The elements of the system interact directly with the system environment, and they can only be connected in an indirect way. In a system composed of the latter, on the contrary, some or even all of the system elements can interact.

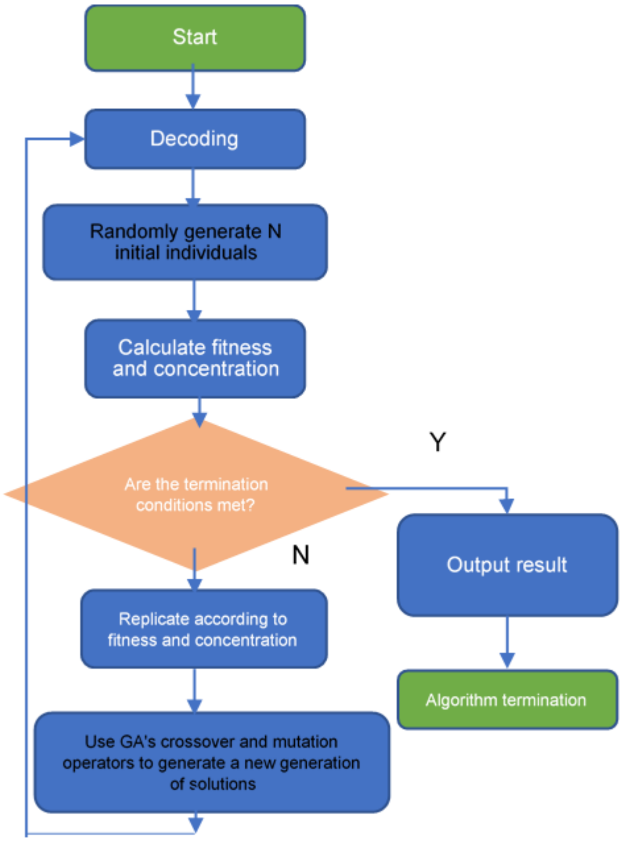


Figure 2. Flow chart of artificial immune algorithm

The basic framework of artificial immune algorithm and genetic algorithm is roughly the same, and both use crossover and mutation two genetic operators to generate the next generation of population. However, there are three major differences between the immune algorithm and the genetic algorithm, that is, the immune algorithm saves the local optimal solution in the population evolution process. As a memory cell, for a given problem, the memory cell generates an initial solution based on the matching degree between the antibody and the antigen. The fitness of the antibody and the concentration of the antibody are selected and copied. Based on this, the immune algorithm can be expected to have the following characteristics:

(1) Maintain the ambiguity of the solution group to ensure that the immune algorithm can search for both the local optimal solution and the global best solution

(2) Maintain the diversity of the search direction of the algorithm, making the optimization process of the immune algorithm more effective.

3. Multi-robot System Coordinated Planning Experiment

Multi-robot collaboration is a complex process. How to effectively organize multi-robot systems so that robots can perform tasks in collaboration is the key to system design. The design of a multi-robot collaboration system generally considers the following aspects of robot capabilities, group architecture, and collaboration rules. The ability of individual robots determines the performance of the entire system. The group architecture determines the relationship constraints between robots and the cooperation rules define the behavior constraints of robots. In this paper, multiple functional modules are designed for experiments to improve the collaborative process of robots so that the handling tasks can be successfully completed.

The neural network behavioral decision-making system is used to control the movement of the robot and conduct research. The performance of the behavioral decision-making system is analyzed from four aspects including the influence of the main parameters of the algorithm, and compared with the application research of the standard genetic algorithm optimized neural network in the multi-robot cooperative handling problem. Through the comparison of simulation results, it is also confirmed that the proposed method is better than the multi-robot control method of algorithm optimized artificial neural network in terms of convergence speed, solution volatility, dynamic convergence characteristics and so on.

3.1. Multi-Robot Handling Simulation Experiment Steps

STEP 1: Concatenate all the substrings of the connection weight of the neural network in a certain order to form the genotype antibody variable;

STEP 2: Set the values of the parameters of the algorithm, the total number of antibodies and the value of the life cycle. Let iterate pointer and set the maximum number of iterations

STEP 3: A random selection method is used to generate antibodies from the antibody variables to form the initial antibody group, and each antibody represents the value of all the connection weights of a neural network.

STEP 4: Initialize the handling environment, generate the lighthouse position, place the target object and the handling robot in the environment randomly, retain this initial environment, and update the environment information in it.

STEP 5: Set the fitness of all antibodies in the antibody group $f_i = 0$; set i=1 (i represents the i-th antibody);

STEP 6: Decode the i-th antibody value into connection weights to construct the i-th artificial neural network NN.

STEP 7: Set j=1;

STEP 8: The neural network NN is used to make decisions on the behavior of mobile robots. And update the environment based on the results of the behavior;

STEP 9: Determine whether di is within the collision range, if yes, adjust the output of the neural network, otherwise continue

STEP 10: Determine whether there is a robot in the grasping state, and stop the robot that has grasped the object, otherwise go to STEP 13;

STEP 11: It is judged whether the robots are all in the grasping state, and if so, it will carry out the synchronous handling movement. Otherwise, go to STEP 13;

STEP 12: Determine the distance between the target object and the lighthouse, if it is, stop moving, otherwise go to STEP 13;

STEP 13: Set $j \leftarrow j + 1$, if $j \leq 30$, z then return to STEP 7

STEP 14: $i \leftarrow i + 1$, If $i \leq m$, you call up the initial hunting environment retained in STEP 4, and go to STEP 6, otherwise, save the maximum, minimum, and average values of the fitness f in this generation of antibody groups and the coordinate information of each step of the robot, use To draw a chart, and then continue;

STEP 15: If t=1, the antibody with the greatest fitness in the population is stored as an elite antibody in the variable, and the fitness of the elite antibody is stored in the variable f (in the early stage of evolution, if the fitness of all antibodies is equal to zero, choose any antibody as the elite antibody), go to STEP 18, otherwise, continue'α

STEP 16: If there is no antibody with the same fitness as the elite antibody in this generation, copy the elite antibody stored in the group to the group, and delete the antibody with the smallest fitness in the group. Otherwise, continueα

STEP 17: If the fitness value of the most adaptive antibody in this generation population is greater than the fitness value of the elite antibody, copy the most adaptive antibody and use it as a new elite antibody to replace the elite antibody stored in it. , And replace the value with the fitness of the new elite antibody. Otherwise, continueα

STEP 18: $f_i \leftarrow f_i + 0.1(i = 1 \sim m)$

Perform operations $f_i \leftarrow f_i + 0.1(i = 1 \sim m)$: To avoid these two situations:(1) When the fitness of all antibodies is zero, the selection operation cannot be performed due to the inability to calculate the expected reproduction rate and selection probability of the antibody; (2) When the fitness of some antibodies is equal to zero, it is expected to reproduce The rate and the probability of selection are also equal to zero, resulting in the antibody being eliminated. In the early stages of evolution, there may be many antibodies with zero fitness. If they are eliminated, leaving only number of antibodies to produce the next generation of colonies, the diversity of the colony will be severely damaged.

STEP 19: According to the definition of antibody similarity, the concentration of each antibody is calculated using the value of the connection weight generated after decoding of each antibody and the fitness value of the antibody;

STEP 20: Calculate the expected reproduction rate of each antibody, and calculate the selection probability of each antibody. According to the selection probability, use the "proportional selection method" to select and copy the antibody group;

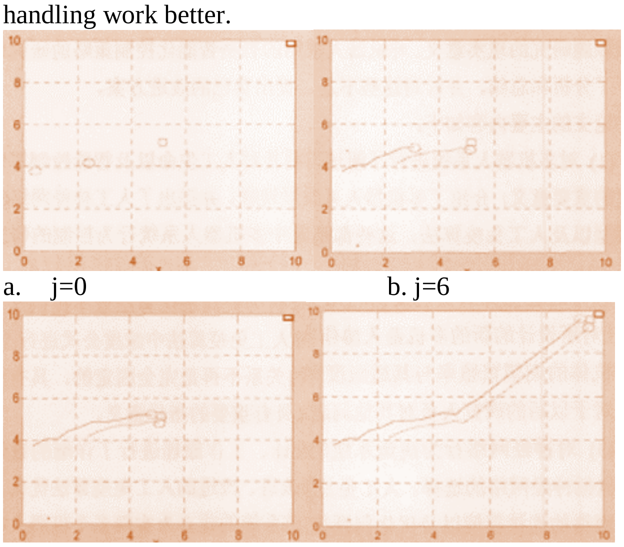
STEP 21: Perform crossover operations P_c on the antibody group according to the given crossover probability;

STEP 22: Perform mutation operations P_m on the antibody population according to the given mutation probability;

STEP 23: Let $t \leftarrow t + 1$, if $t \leq N_c$, return to STEP 1, otherwise, output the curve of the maximum, minimum, and average value of each generation of antibody population fitness f with the algorithm iteration pointer t, and the simulation experiment will stop.

3.2. Simulation Group Diagram of Multi-Robot Cooperative Handling

Figure 3 shows a simulation group diagram in the middle of the algorithm evolution. The figure shows the operation of the robot at four key moments in a life cycle of the robot. At the beginning of the running cycle, the robots and target objects are randomly distributed in the environment. When the robot is moving, one of the robots has moved to the side of the target object, but the other robot is still in the search state and enters the waiting state. The lines in the figure are the trajectories of the two robots. When running to the first step, the second robot has moved to the side of the target object and grabbed the object, and then it enters the synchronization state. In the picture, we can see the trajectory of the two robots synchronously and cooperatively. Finally, the step robot is used to carry the target object to the lighthouse. Experiments show that the algorithm-based neural network controller can control the robot to complete the handling work better.



a. j=0 b. j=6

c. j=1 d. j=2

Figure 3. Mid-term simulation group diagram of algorithm evolution

4. Conclusion

Based on the behavioral decision-making system that combines IGAE and neural network, through computer simulation experiments, the results of the experiments are analyzed and compared, and the performance of this new mobile robot is confirmed from the aspects of convergence speed, solution volatility, and dynamic convergence characteristics. The behavioral decision-making system method can effectively command and control the robot to successfully search for the target object, and it can also carry out the handling work stably. Future work can be considered from the following aspects: Since this article uses a neural network to implement behavioral decision-making and control for all mobile robots, we can let all robots have a suitable artificial neural network in the future, that is, let each robot have its own unique control method. Increase the number of mobile robots and target objects, and increase the difficulty of collaboration. In this research, the robot has almost no intelligence, and further research in this area can be done later, such as adding artificial neural networks and other methods to improve the robot’s self-learning ability and intelligence level.

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References

[1] Wang Shuguo. Discussion on the development trend and future directions of foreign intelligent robots. In the Proceedings of the National Planning Automation Field Development Strategy Seminar, Shenyang Institute of Automation, **1999**, pp. 149-162.

[2] Wang Yuechao. Multi-robot Collaborative System Research Ph.D. Thesis Harbin Institute of Technology, Wang Yuechao Research Status and Development of Collaborative Robotics Robotics, **1998**, Volume 1, number 20, pp. 69-74.

[3] Hofmeyr S A, Forrest S. Architecture for an artificial immune system. Evolutionary Computation, **1993**, Volume 8, number 8, pp. 443-473.

[4] Ojha U, Chow M Y. An Analysis of Artificial Immune System and Genetic Algorithm in Urban Path Planning. **2010**, Volume 7500, number 1, pp. 1064-1069.

[5] Das P K, Pradhan S K, Patro S N, et al. Artificial Immune System Based Path Planning of Mobile Robot. Soft Computing Techniques in Vision Science.

[6] Kadayif I, Kandemir M. Intelligent Mining for Path Planning using Evolutionary Algorithms and Artificial Neural Network for UAV. ACM Transactions on Embedded Computing Systems, **2015**, Volume V4, number 5, pp. 388-414.