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# **Research on Cooperative Encirclement Strategy of Multiple Underwater Robots based on Wolf Swarm Algorithm**

# Xiaolin Luan<sup>1</sup>, Yuting Sun<sup>2\*</sup>

<sup>1</sup> Department of Information Engineering, Shandong Foreign Trade Vocational College, Qingdao, Shandong, 266000, China

<sup>2</sup> Institute of Oceanographic Instrumentation, Qilu University of Technology (Shandong Academy of Sciences), Qingdao, Shandong, 266000, China

\*Corresponding author's e-mail: 181941620@qq.com

Abstract. The problem of multi underwater vehicle cooperative seizing is an important part of the research of multi-underwater-vehicle cooperative task self-organization, which is widely used in military, rescue and other fields. In this paper, the problem of multiple underwater vehicles (AUVs) encircling is a group of AUVs, which can encircle a target body through cooperative cooperation. The stability of the system can be improved by applying the wolf swarm algorithm to the multi underwater robot system. In this paper, we mainly study the problem of multiple underwater vehicles in two-dimensional space. Wolf swarm algorithm abstracts three kinds of swarm intelligence behaviors, calling wandering behavior, summoning behavior and preying behavior, puts forward a new swarm intelligence algorithm by simulating Wolf-swarm predation. The effectiveness of the algorithm is verified by numerical simulation.

## 1. Introduction

The problem of multi robot coordination and cooperation is one of the hot spots in the research of multi robot system. Multi robot pursuit is an ideal platform to study the coordination and cooperation of multi robots in multi-agent robot system. It mainly studies the optimal cooperative pursuit algorithm in which multiple pursuers can avoid conflicts and maximize profits through cooperation and coordination in the dynamic process of capturing multiple fleeing people.

As an ideal platform to explore the cooperation and coordination of multi-agent in the distributed system, the multi robot pursuit and escape problem is to study how to guide a group of autonomous mobile robots (pursuers) to cooperate with each other to capture another group of mobile robots (hereinafter referred to as targets or escapees), while the real robot pursuit and escape system is a real-time vision part Multi robot distributed system with multi discipline and multi domain knowledge, such as management, wireless communication, multi robot control and cooperation, real-time dynamic path planning, etc[1]. In the pursuit problem, the escape target needs the cooperation of multiple pursuers to capture, and it involves the confrontation between the pursuer and the escape robot groups[2]. In the process of pursuit, the situation is always changing. Each robot must understand the dynamic changes of the environment in real time, judge the current confrontation pattern through real-time knowledge processing, and make decisions such as changing roles, regrouping or formation in time. Therefore, the pursuit problem is a typical problem of real-time knowledge processing in dynamic environment, which has been widely concerned but has not been solved so far. It is also a general problem to study the evolution of multi-agent cooperation and coordination strategy and

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confrontation strategy[3].

At present, there are several typical methods of single target pursuit in the research results of the same conditions between the fugitive and the pursuer: Benda [4] and others first proposed the cooperative pursuit of single prey based on the grid model in the known environment. Four agents in the grid model surround and capture the escaping target by occupying four adjacent grids around an agent. The purpose of the study is to evaluate the efficiency of several cooperation and control algorithms. This kind of right angle game model, which only allows horizontal or vertical movement of both sides of chasing and escaping, is a rough discretization scheme. Yamaguchi uses the inclusion feedback control law to coordinate the motion of multiple mobile robots, and uses formation vector control group formation to achieve the capture and encirclement of single target[4]. Shakernia proposed to combine map exploration and pursuit into a problem, and completed the single target pursuit task in the unknown environment in the probability framework[5]. In order to realize the multi mobile robot's encirclement in the unknown environment, Cao models the task of encirclement as five states: queuing, random search, encirclement, capture and prediction, and puts forward the strategies of queuing, search, encirclement, capture and direction optimization. On this basis, they also put forward a distributed control method of multi robot based on local interaction[6]. Chen et al. Studied the problem of the consistency of the surrounding following target. For the formation of the target, the tracker formed similar formation on the periphery [7].Under the support of NSFC, researchers from Northwestern Polytechnic University have carried out research on the formation navigation control of multiple underwater robots and cooperative positioning of multiple underwater robots[8].

#### 2. Description of pursuit problem

In this paper, the problem of multiple AUVs entrapment is that a group of AUV cooperate to entrap a single target. By simulating the way of wolf swarm preying, and then puts forward a new swarm intelligence algorithm. The effectiveness of the algorithm is verified by numerical simulation.

Firstly, a map model including obstacles is established, then a dynamic target escape model is established. Based on the wolf swarm algorithm, a cooperative strategy for capturing dynamic targets is given. The successful mark of dynamic target seizing is established: at least 3 underwater robot can detect the invasion target, then multi robots should complete the seizing on the premise of avoiding obstacles.

### 3. Establishment of wolf swarm algorithm model

Let the hunting space of wolves be a  $N \times D$  Euclidean space, where N is the total number of following wolves in wolves, and D is the number of variables to be optimized. The state of a following wolf *i* can be expressed as  $X_i = (X_{i1}, X_{i2}, ..., X_{id}, ..., X_{iD})$ , Where  $X_{id}$  is the position of the *i* following wolf in the d(d = 1, 2, ..., D) dimensional variable space for optimization. The odor concentration perceived by the following wolves is y = f(x), where y is the objective function value; the distance between the following wolves p and q is defined as the Mahattan distance between their state vectors:

$$L = (p,q) = \sum_{d=1}^{D} \left| X_{pd} - X_{qd} \right|$$
(1)

Of course, other distance measures can be selected according to specific problems. In addition, because the maximum and minimum problems can be converted to each other in practice, for the convenience of discussion, the maximum problems are discussed below.

The following will introduce the basic algorithm model of wolf swam. Firstly, the whole preying activity of wolf swam is abstracted into three intelligent behaviors, which are wandering behavior, summoning behavior and preying behavior. On this basis, the preying behavior of wolf pack is abstracted as the optimization process.

#### 3.1 The rule of the Leader Wolf

In the initialization space, the following wolf with the optimal objective function value is the lead wolf. In the iteration process, the objective function value of the optimal wolf after each iteration is compared with the value of the lead wolf in the previous generation. If it is better, the position of the lead wolf is updated. If there are multiple wolves at this time, one wolf is randomly selected as the lead wolf. The lead wolf does not perform three intelligent behaviors and goes directly to the next iteration until it is replaced by other stronger following wolves.

#### 3.2Wandering behavior

In the solution space, except the lead wolf, the best  $S_num$  wolves is regarded as following wolves,

search for prey in solution space,  $S_num$  takes the random integer between  $\left[\frac{n}{(\alpha+1)}, \frac{n}{\alpha}\right], \alpha$  is the following wolf proportion factor. Following wolf *i* first perceives the odor of prey in the air, that is, calculates the odor concentration  $Y_i$  of prey at the current position of following wolf. If  $Y_i$  is greater than the odor concentration  $Y_{lead}$  perceived by the lead wolf, it indicates that the prey is relatively close to the following wolf *i* and the following wolf is most likely to catch the prey. Then  $Y_{lead} = Y_i$ , following wolf *i* to replace the lead wolf and initiate the summoning behavior; if  $Y_i < Y_{lead}$ , following wolf makes independent decision, that is, following wolf to advance one step in *h* directions (the step at this time is called the walk step  $step_a$ ) and record the odor concentration of the prey perceived before and after each further step and then return to the original position, then follow the wolf *i* in the *d* dimensional space after advancing in the p(p = 1, 2, ..., h) directions

$$X_{id}^{p} = X_{id} + \sin(2\pi \times \frac{p}{h}) \times step_{a}$$
<sup>(2)</sup>

At this time, the odor concentration of the prey perceived by the following wolf is  $Y_{ip}$ , select the direction with the strongest odor and greater than the odor concentration of the current position to move forward, update the state  $X_i$  of the following wolf, repeat the above walk behavior until the odor concentration  $Y_i > Y_{lead}$  or the number of walks T of the prey perceived by the following wolf reaches the maximum walk times  $T_{max}$ . It should be noted that there are differences in the way of searching for prey of each following wolf, and the value of h is different. In fact, the random integer between  $[h_{\min}, h_{\max}]$  can be taken according to the situation, the h is larger , the tracking wolf is more careful, but at the same time the speed is relatively slower.

#### 3.3Summoning behavior

The lead wolf initiates the summoning behavior by howling, and gathers the surrounding  $M_num$  following wolves to move towards the position of the lead wolf rapidly, among which  $M_num = n - S_num - 1$ ; the following wolves who hear howling quickly approach the position of the lead wolf with relatively large raid step  $step_b$ . When following wolf *i* is k+1 iteration, the position in the d-dimensional variable space is

$$X_{id}^{k+1} = X_{id}^{k} + step_{b}^{p} \times (g_{d}^{k} - X_{id}^{k}) / |g_{d}^{k} - X_{id}^{k}|$$
(3)

In the formula,  $g_d^k$  is the position of the k iteration lead wolf in the d dimensional space. Formula (3) is composed of two parts, the former is to follow the current position of the wolf, reflecting the basis of hunting; the latter is to follow the trend of the wolf gradually gathering to the position of the lead wolf, reflecting the command of the lead wolf to the wolves.

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On the way of the prey, if the following wolf perceives the odor concentration of the prey is  $Y_i > Y_{lead}$ , then  $Y_{lead} = Y_i$ , the following wolf will turn into the lead wolf and initiate the summoning behavior; if  $Y_i < Y_{lead}$ , then the following wolf *i* will continue to prey until the distance *dis* between the following wolf and the lead wolf is less than  $d_{near}$  and join the prey ranks of the prey, that is to say, the following wolf will turn into prey. The *d* variable which to be optimized is the value range of  $|\min_d, \max_d|$ , then the judgment distance  $d_{near}$  is estimated by the formula:

$$d_{near} = \frac{1}{D \bullet \omega} \bullet \sum_{d=1}^{D} \left| \max_{d} - \min_{d} \right|$$
(4)

In the formula,  $\omega$  is the distance determining factor, and its different values will affect the convergence speed of the algorithm. Generally speaking,  $\omega$  increases the convergence speed of the algorithm, but the excessive  $\omega$  makes it difficult for the following wolf to enter the preying behavior, and lacks the fine search for the prey. The summoning behavior embodies the information transmission and sharing mechanism of wolf pack, and integrates the social cognitive perspective. Through the "follow" and "response" of other individuals in wolf pack to the excellent group, it fully shows the social and intelligent nature of the algorithm.

#### 3.4Preying behavior

After the prey, the following wolf is close to the prey. At this time, the head wolf should unite with the following wolf to make a close prey on the preying in order to catch it. Here, the position of the wolf closest to the prey, i.e. the head wolf, is regarded as the moving position of the preying. Specifically, for the k iteration wolves, the position of preying in the d dimensional space is  $G_d^k$ , the preying behavior of the wolves can be expressed by the following equation

$$X_{id}^{k+1} = X_{id}^k + \lambda \cdot step_c^d \left| G_d^k - x_{id}^k \right|$$
<sup>(5)</sup>

In the formula,  $\lambda$  is the random number evenly distributed among [-1,1]; *step<sub>c</sub>* is the preying step length when following wolf *i* to execute the preying. If the odor concentration perceived by the following wolf after the prey is greater than that perceived by its original position, the position of the following wolf will be updated; otherwise, the position of the following wolf will not change.

If the value range of the d variable to be optimized is  $|\min_d, \max_d|$ , then the three intelligent behaviors involve walk step  $step_a$ , raid step  $step_b$  and prey  $step_c$ , the step size in the d dimension space is the following relationship:

$$step_{a}^{d} = \frac{step_{b}^{d}}{2} = 2 \cdot step_{c}^{d} = \frac{\left|\max_{d} - \min_{d}\right|}{S}$$
(6)

In the formula, S is the step factor, which indicates the fineness of the following wolf searching for the optimal solution in the solution space.

#### 4. Simulation

In this section, the simulation experiments based on MATLAB software and auv platform are recorded, and the simulation experiment data based on the basic wolf swarm algorithm are shown respectively. In this paper, a two-dimensional 20 \* 20 encirclement map is simulated, and obstacles are randomly generated. One encirclement target and four cooperative encirclement robots are set up. The initial setting of the simulation environment is shown in Figure 1. The robot needs to achieve the encirclement of the target on the premise of avoiding obstacles. The simulation results show that the four encircling robots successfully complete the target encirclement through the wolf swarm algorithm, as shown in Figure 2.

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# 5. Conclusion

In this paper, a multi AUV round up strategy based on the wolf swarm algorithm is proposed. The objective adaptive function is set considering the environmental factors (location, income, etc.). Each Hunter optimizes the task allocation through cooperative feedback, which greatly improves the convergence performance of the algorithm. Moreover, when dealing with the task cooperation of large-scale robot, the tracking time is significantly shorter than the existing algorithm.

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