Multi-sensor cross cueing technology based on grey wolf algorithm

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Abstract. In order to solve the problem of poor convergence and low precision of the current Multi-sensor Detection Network algorithm, a multi-sensor cross cueing technology based on Grey Wolf algorithm is proposed. By endowing the grey wolf with autonomous decision-making ability, the algorithm can jump out of the local optimal solution as soon as possible, and the convergence degree of the algorithm is improved. The simulation results show that the algorithm can find the optimal solution in a short time and maintain good stability, and the optimization ability is further strengthened. By comparing with other algorithms, it is more effective to prove that the algorithm has better solution quality.

1. Introduction
The formation of multi-sensor network belongs to the multi-objective assignment problem in multi-sensor management. The concept of multi-sensor cross cueing technology is systematically proposed in document [1]. The application of this technology in target detection improves the reliability and timeliness of detection. In document [2], the discrete particle swarm optimization (DPSO) algorithm is proposed in multi-sensor management. In the application of multi-objective allocation, the algorithm has good stability; literature [3] proposes an algorithm based on colored Petri nets, which proves the superiority of the algorithm; literature [4] considers the asynchronism of communication, proposes a DTC algorithm for distributed tasks, and solves the sensor problem considering asynchronous communication of sensors. Resource management problem; document [5-6] mainly uses contract network and improved contract network algorithm to achieve multi-sensor multi-objective allocation. Although the convergence speed of the algorithm is faster, its solving ability needs to be further enhanced; document [7] proposes an energy-efficient distributed sensor management algorithm with good convergence characteristics; document [8] based on the theory of artificial bee colony algorithm, an improved artificial bee colony algorithm with stronger searching ability is proposed, and the convergence and robustness of the algorithm are validated effectively.

From the above literature, it can be concluded that in the current multi-sensor network formation algorithm, although the convergence and stability of the algorithm is good, the quality of the algorithm needs to be further strengthened, and the optimization ability of the algorithm is weak, the real-time performance and effectiveness are poor. In view of the above problems, a multi-sensor network scheme based on improved grey wolf algorithm is proposed.
2. The establishment of the model

Suppose that the Multi-sensor Network contains \( m \) sensors, and there are \( n \) targets at a certain time. Among them, at the moment \( k \), the sensor network set up for the target \( t \) is recorded as: \( S_t = \{s_{1}, s_{2}, ..., s_{m}\} \). Let the detection network \( C \) be a \( m \times n \) one-order 0-1 matrix, then we have:

\[
c_{ij} = \begin{cases} 
0, & \text{Sensors are not added to the dynamic network of the target} \\
1, & \text{Sensors are added to the dynamic network of the target} 
\end{cases}
\]

The detection accuracy \( A \) of the target by the sensor is a matrix of \( m \times n \) order, which \( a_{ij} \) is the detection accuracy of the target \( t_j \) in sensor \( s_i \). The accuracy of the sensor on the target is calculated from equation (1).

\[
a_{ij} = \frac{n_{ij}}{NT}
\]

In the formula, \( n_{ij} \) indicates the number of targets detected at a certain time, \( t_j \) indicates the effective time at which the target is detected at a certain time, \( N \) indicates the total number of probe targets required by the network, and \( T \) indicates the total time of the target motion.

When using a sensor \( s_i \) to detect a target, the energy consumption is:

\[
\cos t(s_i) = -\exp\left(-\frac{l(s_i)}{\alpha_i \times r(s_i) + \beta_i}\right)
\]

Where \( \alpha_i \) and \( \beta_i \) are constants, take \( \alpha_i = 0.01, \beta_i = 0.1 \). \( l(s_i) \) is the number of targets that can be detected at the same time, and \( r(s_i) \) is the farthest detection distance.

When establishing the objective function of the multi-sensor detection network model, it should be made to meet the total detection accuracy \( A \) of the multi-sensor detection network \( C \), and the maximum total energy consumption \( COST \) of the network at the same time is the minimum. Therefore, the following objective function can be obtained:

\[
\max A = \max \left\{ \sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij} \right\}
\]

\[
\min COST = \min \left\{ \sum_{i=1}^{m} \sum_{j=1}^{n} \cos t_{ij} \right\}
\]

The constraints are:

\[
\sum_{j=1}^{n} c_{ij} \leq M_j
\]

\[
\sum_{i=1}^{m} c_{ij} \geq 1
\]

The evaluation index of the multi-sensor detection network refers to the value of the optimal solution of the multi-sensor detection network, that is, the fitness value. The fitness value should be proportional to the total target detection accuracy \( A \) and inversely proportional to the maximum total energy consumption \( COST \), so it is used to represent the most of the detection network. The value of the optimal solution has the following formula:

\[
\Phi(X) = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} \cos t_{ij}}
\]
3. Grey wolf algorithm

The hunting behaviour of grey wolf population mainly includes following, pursuing and approaching the prey; hunting and encircling the prey until the prey no longer moves. The mathematical models surrounding prey are as follows:

\[ D = \left| Cg_{i}^{t} - \lambda_{i} \right| \]  
\[ X_{i+1}^{t} = X_{i}^{t} - Ag_{i} \]  

Where \( D \) indicates the distance between the prey and the wolf, \( t \) indicates the current iteration, \( X_{i}^{t} \) indicates the position vector of the prey, \( A \) and \( C \) are the reference vectors. \( A = 2ag_{i} - a \), \( C = 2gr_{2} \), where \( a \) decreases from 2 linear to 0 in the iteration process, and \( r_{1}, r_{2} \) is a random vector on \([0,1]\).

Grey wolf population can use \( \alpha, \beta, \delta \) wolf position to determine the location of prey. The formula for updating its position is as follows:

\[ D_{i} = \left| Cg_{i}^{j} - \lambda_{i} \right| \]  
\[ X_{i}^{t} = X_{i}^{t} - Ag_{i} \]  
\[ X_{i+1}^{t} = \frac{X_{1} + X_{2} + X_{3}}{3} \]  

To illustrate the above formula, figure 1 gives a graphical representation of the location of the grey wolf population.

![Figure 1. The process of own position updating](image)

The realization of basic Grey Wolf algorithm mainly depends on changing the value to realize the change of parameters. In the process of decreasing the equivalent value from 2 to 0, the corresponding value also obtains any value in \([-2a, 2a]\). When \( |A| \leq 1 \), the wolves besieged the prey. On the contrary, when \( |A| > 1 \), the wolves dispersed and continued to search for the optimal solution, and then they would be trapped away from the optimal solution. In the case of searching for local optimal solution, the location of \( \alpha, \beta, \delta \) wolves plays an important role in the grey wolf population, which may lead to the existence of wolves in a rush and scatter situation.

In view of the situation that the basic Grey Wolf algorithm proposed above is easy to make the optimization process fall into local optimal solution, a new improved grey Wolf algorithm is proposed. In grey wolf population, each wolf can follow the previous method to find the optimal solution, but at the same time each wolf can follow the changes of the external environment. Have the ability of
independent decision-making, through the analysis of the position of wolves higher than their own level, real-time decision-making, change their position to achieve the search process of the optimal solution. According to the classification of wolves based on the basic wolf swarm algorithm, wolves are divided into four levels. Assuming that the decision-making factor is $D_i$, the total number of wolves is recorded as $R$, the level $L_i$ at which the first wolf is at the moment $t$, the decision-making model of each level is given as follows:

$$D_i = \frac{R - L_i}{R - 1}$$ (13)

The procedure of the algorithm is shown below.

4. Simulation
Assuming that there are 10 sensors in a sensor network and eight enemy targets are detected at the same time, the detection capability of each sensor is given below, as shown in Table 1.
### Table 1. Detecting precision of sensors to targets

| Sensor | T1  | T2  | T3  | T4  | T5  | T6  | T7  | T8  | Level | Ability | Cost |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-------|---------|------|
| S1     | 0.981 | 0.031 | 0.413 | 0.386 | 0.987 | 0.659 | 0.678 | 0.614 | 0.05 | 8 | 0.03 |
| S2     | 0.439 | 0.861 | 0.543 | 0.471 | 0.259 | 0.546 | 0.757 | 0.605 | 0.11 | 6 | 0.03 |
| S3     | 0.171 | 0.196 | 0.969 | 0.986 | 0.071 | 0.800 | 0.743 | 0.127 | 0.08 | 5 | 0.02 |
| S4     | 0.008 | 0.231 | 0.074 | 0.163 | 0.015 | 0.035 | 0.392 | 0.713 | 0.21 | 8 | 0.04 |
| S5     | 0.277 | 0.093 | 0.047 | 0.944 | 0.499 | 0.649 | 0.655 | 0.632 | 0.15 | 10 | 0.02 |
| S6     | 0.442 | 0.915 | 0.275 | 0.462 | 0.212 | 0.234 | 0.171 | 0.097 | 0.12 | 8 | 0.03 |
| S7     | 0.040 | 0.162 | 0.617 | 0.942 | 0.802 | 0.970 | 0.600 | 0.757 | 0.07 | 12 | 0.04 |
| S8     | 0.051 | 0.353 | 0.397 | 0.330 | 0.569 | 0.915 | 0.147 | 0.764 | 0.06 | 12 | 0.02 |
| S9     | 0.043 | 0.081 | 0.706 | 0.888 | 0.329 | 0.934 | 0.042 | 0.157 | 0.07 | 8 | 0.03 |
| S10    | 0.655 | 0.596 | 0.387 | 0.031 | 0.516 | 0.171 | 0.715 | 0.670 | 0.08 | 8 | 0.02 |

### 4.1. Comparison of optimal solutions of coalition schemes before and after algorithm improvement

The grey wolf algorithm and the improved grey wolf algorithm are used to calculate the optimal solution of the multi-sensor network, and 100 Monte Carlo experiments are carried out. The results are shown in Figure 3 and the alliance scheme is shown in Table 2.

#### Table 2. Multi-sensor detective coalition cases

| Target | Basic Algorithm | Improved Algorithm |
|--------|----------------|--------------------|
| 1      | 1, 2, 3, 4, 5  | 1, 3, 4, 5, 8      |
| 2      | 2, 4           | 3, 4, 5, 8         |
| 3      | 1, 3           | 3, 4, 5, 6, 8      |
| 4      | 3              | 3, 4, 6, 8         |
| 5      | 3, 5           | 3, 4, 6, 8         |
| 6      | 2, 3, 5        | 3, 4, 6, 8         |
| 7      | 2, 5           | 3, 4, 6, 8         |
| 8      | 2, 3, 4, 6     | 3, 4, 6, 8         |

From Figure 3, it can be seen that the improved grey wolf algorithm and grey wolf algorithm can effectively solve the optimal solution of multi-sensor network. The improved grey wolf algorithm achieves stability in 36 iterations. The optimal solution of the alliance is 8.631. The grey wolf algorithm achieves stability after 57 iterations and the optimal fitness of the alliance is 6.756. The simulation results show that the improved grey wolf algorithm has better convergence than the
improved grey wolf algorithm and detects the alliance. The coalition fitness is higher, which shows that the improved grey wolf algorithm has improved the search ability.

4.2. Comparison of different algorithms
The improved wolf swarm algorithm proposed in this paper is compared with artificial bee swarm algorithm and particle swarm optimization algorithm. Fifty Monte Carlo experiments are carried out to study the influence of different algorithms on the optimal solution of network scheme. The experimental results are shown in Figure 4 below.

![Figure 4. The comparison of three algorithms](image)

The simulation results of figure 4 shows that the convergence of the three algorithms is very good. The algorithm in this paper achieves the optimal coalition solution after 13 iterations, with the fitness value of 9.633, and the running time of the algorithm is the shortest; the improved bee colony algorithm achieves the optimal coalition solution after 18 iterations, with the fitness value of 7.515; and the particle swarm optimization algorithm runs the longest. After 21 iterations, the optimal solution is obtained, but the coalition fitness is the lowest at this time. This shows that the algorithm has short running time, fast convergence speed and stability, which can make the detection coalition maintain a better fitness value.

5. Conclusion
This paper proposes a multi sensor network scheme based on Improved Grey Wolf algorithm. Firstly, the target observation model is established. Secondly, the multi-sensor target detection model is established and the objective function and evaluation function of the alliance are put forward. Through the improvement and optimization of the basic grey wolf algorithm, the grey wolf has the right of autonomous decision-making to jump out of the local optimal solution and enhance the optimization degree of the algorithm to the optimal solution of the alliance. The Improved Grey Wolf algorithm has the advantages of simple design idea, high practicability, high solution quality and good convergence.

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References
[1] D D, R C A. Proceedings of the 2007 American Control Conference. 2007: 5406-5411.
[2] DP, CP. Service orientation in holonic and multi-agent manufacturing and robotics studies in
[3] A, G. International Journal on Software Tools for Technology Transfer, 2016, (17): 1-22.
[4] Z. Li, C. Liu, F. Meng, K. Zhou, Proc. Inst. Mech. Eng. C 227, 1481 (2013)
[5] S. Li, Z. Liu, IEEE Trans. Ind. Electron. 56, 3050 (2009)
[6] H. Wu, J. Hu, Y. Xie, Characteristic model-based intelligent adaptive control (China Science and Technology Press, Beijing, 2009)
[7] S. Li, H. Du, X. Yu, IEEE Trans. Auto. Ctrl. 59, 546 (2014)
[8] M S, M S M, L A. Advances in Engineering Software, 2014, 69(3) : 46-61.
[9] K G M, K V. Journal of Computational Science, 2015, 8: 109-120.
[10] SS, M S Z, MS M. Neural Computing and Applications, 2015, 26(5): 1256-1263.