Multi-sensor scheduling method based on Cuckoo and Particle Swarm optimization algorithm

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Abstract. In order to solve the problem that particle swarm optimization (PSO) tends to fall into the local optimal solution and the convergence speed is slow when solving multi-sensor resource scheduling model, a cuckoo particle swarm optimization (CPSO) algorithm is proposed on the basis of PSO. On the basis of target tracking model, the multi-sensor scheduling model is established. Then the LEVY flight was introduced from cuckoo algorithm into particle swarm algorithm, the algorithm can jump out of the local optimal solution as soon as possible and improve the convergence speed and accuracy of the algorithm. The simulation results show that the improved algorithm is effectively improved in terms of convergence speed and accuracy, and is applied to the solution of sensor scheduling model to further enhance the optimization ability and achieve good results.

1. Introduction
Since the 20th century, with the rapid development of communication technology, multi-sensor data fusion technology has been widely used in acquisition of detection information and data acquisition[1-2]. In order to obtain the optimal data, it is very important to allocate and utilize the limited sensor resources reasonably. Sensor scheduling can improve the performance of multi-sensor system and improve its operation rate. Therefore, reasonable sensor scheduling is a research hotspot in the field of maneuvering target tracking.

In this field, most researches have the calculation methods of tracking accuracy for all targets under a given sensor sequence. For example, the particle filter method proposed by Chakravarty [3] and Qiao Chenglin [4] proposed to establish a target tracking and radiation control model based on partial Markov decision process (POMDP), calculate the detection probability of new-born targets with randomly distributed particles, and predict the long-term tracking accuracy with a posteriori Kr Latin American lower bound (pcrlb), The branch and bound algorithm based on greedy search is used to solve the optimal scheduling sequence. In addition, in recent years, emerging intelligent algorithms have also begun to be studied for sensor scheduling problems, such as Yan Zhiwei, Niu Yifeng [7] and Guo Haobo, Wang Yinglong [8] and Li Guohui [9] respectively used parallel tabu genetic algorithm, genetic simulated annealing algorithm and differentiated particle swarm optimization algorithm to solve the sensor scheduling problem under different backgrounds.

Sensor scheduling under multi-sensor and multi-target tracking task is a complex combinatorial optimization problem. At present, swarm intelligence algorithm, such as genetic algorithm, simulated annealing algorithm and ant colony algorithm, are commonly used to solve large-scale optimization
problems. All of these algorithms can obtain the approximate optimal solution within the permissible time range. Particle swarm optimization algorithm is based on the population yuan heuristic intelligent optimization algorithm, by using the particle's problem space to find individual optimal solutions and local optimal solutions, the theory of the algorithm process is simple, easy to implement, and it is widely used in function optimization, data mining and other fields, but this method is easy to fall into local optimum, late and slow convergence speed. Cuckoo Search is a bionic algorithm that imitates Cuckoo behavior. LEVY flight in this algorithm can travel globally to conduct global Search, so it can converge to global optimal and has been widely used. Therefore, in order to improve the convergence speed and accuracy of multi-sensor scheduling algorithm, CS algorithm is introduced in the PSO algorithm process to improve the algorithm population diversity, so as to improve its convergence time and accuracy and find the global optimal solution. The simulation results show that CPSO algorithm can solve the multi-sensor scheduling model under the background of target tracking with faster convergence speed and higher accuracy.

2. Model building

Under the background of multi-sensor and multi-tracking target task, the sensor scheduling needs to comprehensively consider various index requirements. Suppose there are M sensors in this scheduling task, and there are N incoming targets at a time. Is a binary variable, indicating whether the task scheduling has been completed. If the task T is completed within the total time K beyond the specified step size, the detection task is performed, then =1, indicating that the task has been completed.

2.1. The tracking accuracy

The tracking accuracy of sensor S to target T is calculated by Formula (1) (2). The moment when the sensor dispatching ends is K. For single target t, the estimation error covariance matrix of time k can be calculated by using the target tracking model. The tracking accuracy needs to consider all target tracking accuracy comprehensively. The tracking accuracy of task t can be calculated by using the trace of error covariance matrix.

\[ d' = 1 / \sqrt{\text{Trace}(P_1(K | K))} \]  

(1)

Let M be the total number of targets to be tracked and \( C_{\alpha} \) is the average precision of all tracking targets:

\[ C_{\alpha} = \frac{\sum_{i=1}^{M} d'}{M} \]  

(2)

2.2. Task completion rate index

In multi-target tracking scenarios, limited sensor resources may not be able to meet the tracking requirements of all targets, so it is necessary to distinguish the importance of targets in order to prioritize the tracking of key targets. Also, each observation target has its own priority, which is obtained by its model information. The priority of each target is different.

Set the priority order of target T as, which can be calculated by the sum of the priorities of the completed tracking target tasks and the sum of the priorities of all the tracking target tasks.

\[ C_{\beta} = \frac{\sum_{i=1}^{N} x_i p_i}{\sum_{i=1}^{N} p_i} \]  

(3)

2.3. Energy consumption of sensors

The energy consumption of the sensor refers to the energy consumed by the sensor during the detection of the target. The energy of the sensor is limited, so detection should be carried out to the maximum extent within the energy consumption range of the sensor. The energy consumption of sensor resources is defined as follows:
\[ C_\mu = \sum_{i=1}^{N} \frac{1}{1 + \exp\left(\frac{1}{\alpha_i \times c_j + \beta_i \times l_i}\right)} \]  

\[ (4) \]

2.4. Objective function

\[ \text{max } f = \gamma_\alpha C_\alpha + \gamma_\beta C_\beta + \gamma_\mu C_\mu \]  

The output objective function value represents the matching degree between the sensor and the target at the current moment. When the optimal function value is reached, the scheduling relationship between the sensor and the target is established.

2.5. Constraint condition

This study is conducted under the following constraints:

1. Where \( a \) represents the shortest observation time.

\[ T_{K+1} - T_K \geq a \]  

\[ (6) \]

2. The sensor resources used can not exceed the resources available for the sensor

\[ \sum x_{ij} < \sum MS_{ij} \]  

\[ (7) \]

3. Optimization algorithm

3.1. Particle swarm algorithm PSO

Particle Swarm Optimization is a new Evolutionary Algorithm developed by J. Kennedy and R. C. Eberhart in recent years. This algorithm is based on the population meta-heuristic intelligent optimization algorithm, by using the particle problem space to find the individual optimal solution and the local optimal solution, the algorithm theory is simple, easy to implement, widely used in many fields.

Firstly, a population with a particle number of \( N \) is selected from the D-dimensional search space. Particle is, its position vector is \( l \), its velocity vector is \( v \), and the best position searched by particle in history is defined as \( p \). The whole population has a global best position \( g \). During each iteration, the following formula is used to update the particle velocity and position respectively

\[ \begin{align*}
    v_{ij}(k+1) &= v_{ij}(k) + c_1 r_1 (p_{ij}(k) - l_i(k)) \\
    &+ c_2 r_2 (g_{ij}(k) - l_i(k)) \\
    l_{ij}(k+1) &= l_{ij}(k) + v_{ij}(k + 1)
\end{align*} \]  

\[ (8) \]

\( c_1, c_2 \) are constants, are cognitive factors and memory factors, and \( r_1, r_2 \) are random Numbers on [0,1].

\[ p_i(k+1) = \begin{cases} l_i(k+1), f(l_i(k+1)) < f(p_i(k)) \\ p_i(k), \text{otherwise} \end{cases} \]  

\[ (9) \]

\[ g(k+1) = \text{arg min } f(p_i(k + 1)) \]  

\[ (10) \]

3.2. Cuckoo Search algorithm CS

Cuckoo Search is Xin - she Yang and Suash Deb proposed an imitation of the Cuckoo "parasitic" bionic algorithm, female Cuckoo don't nesting, brooding, raising young, but their eggs secretly is produced in the nests of other birds are also referred to as host, incubation and brood on his behalf by the host, this kind of behavior is called "parasitic" it.

The algorithm has simple flow, fast calculation speed and few parameters. Cuckoo search algorithm can not only search locally, but also travel around the world by Levy flight to conduct
global search, so that convergence reaches global optimal. Cuckoo algorithm is based on the following three assumptions:

A) Each cuckoo hatches an egg one at a time and places it in a randomly selected nest;
B) Nests of higher quality are considered the best nesting sites and will be passed on to the next generation;
C) There are a certain number of selected host nests, and cuckoo eggs may be found by the host, leading to the failure of incubation

Based on the above premise, the nest location update formula is:

$$x_i^{(t+1)} = x_i^t + \alpha \odot L(\lambda)$$

Where, $$x_i^{(t+1)}$$ is the position of the new generation nest, $$x_i^t$$ is the position of the its nest in the T iteration; is the step size, $$\alpha$$ is the control parameter, usually 1; $$L(\lambda)$$ is the search path, satisfying Levy distribution:

$$L(\lambda) \sim u = t^{-\lambda}$$

3.3. Optimization algorithm
PSO algorithm is simple in phase calculation, but PSO algorithm is easy to fall into the local optimal solution and slow in the later period. In order to solve this problem, levy flight of cuckoo algorithm was introduced into PSO algorithm to improve the algorithm’s overall searching ability and quickly reach the global optimal solution. The optimized CPSO algorithm solves the multi-sensor resource scheduling model in the following process.

$$R(k + 1) = d \times x_i(k + 1) + (1 - d) \times l_i(k + 1)$$

$$x_i(k + 1) = R_i(k + 1)$$

$$l_i(k + 1) = R_i(k + 1)$$

The steps of cuckoo particle swarm optimization algorithm are as follows:

1. Initialize the objective function $$F(x)$$ and generate the initial population $$N$$.
2. Evaluate fitness.
3. Use Equations (7) - (12) for each task to find the new solution of CS and PSO search respectively.
4. Repeat step 3 until the stop condition is met.
5. Use the formula(13) to find the new solution.
6. If the value of the solution $$S(k + 1)$$ is less than $$f(S(k))$$, then replace the solution to I with the former solution.
7. Discard nests according to the probability of discovery
8. Assign solutions of CS and PSO according to Equation (14)
9. Use Equations (9) - (10) to update the individual optimal solution and the global optimal solution
10. Retain and sort the optimal solution
11. Output scheduling scheme
12. end

4. The simulation conditions
Suppose there is a square area what coordinate range is from (0,0) to (1000,1000). Five detection sensors are set in this area. It is assumed that within a period of 0s~1000s, 5 hostile attacking targets will appear in this area, and the observation priority can be obtained according to the model information. Assuming that each sensor can detect any target during detectable time. Parameters of particle swarm optimization algorithm and cuckoo search algorithm were set: the maximum number of iterations was 100, the cognitive factor was 0.6, and the social learning factor was 0.2.
In order to verify the effectiveness of the improved algorithm, the CPSO algorithm and PSO algorithm were simulated and analyzed from the four aspects of performance, convergence speed and convergence.

a. Performance analysis

The number of iterations was set as 100. Ten groups of experiments were conducted on the two algorithms respectively. The experimental results are shown in the table below.

| Number | PSO   | CPSO  |
|--------|-------|-------|
| 1      | 0.63872| 0.6449|
| 2      | 0.6327 | 0.6386|
| 3      | 0.6373 | 0.6405|
| 4      | 0.6385 | 0.63852|
| ......  | 0.6371 | 0.6410|
| ......  | 0.6364 | 0.6391|
| ......  | 0.6355 | 0.6421|
| ......  | 0.6387 | 0.6415|
| ......  | 0.63854| 0.63854|
| ......  | 0.6381 | 0.6381|
| Mean value | 0.6371 | 0.6404|

By the information available in the table, use the CPSO algorithm has obtained the best fitness value is higher than the desires of PSO algorithm of optimal fitness value, because the CPSO algorithm in differential evolution after operation in order to gain more genetic information, generate new individuals, that can increase the diversity of population in the iteration, so as to avoid falling into local optimum, and therefore has better ability of optimization solution of the higher performance.

b. The rate of convergence

Compared with the PSO algorithm, the improved CPSO algorithm has a higher fitness value and can converge to the optimum faster.

c. Convergence
The comparison of the two graphs shows that the optimal fitness function of the improved algorithm is higher than that of PSO Algorithm, and the convergence is also better.

5. Conclusion

Particle swarm optimization (PSO) and cuckoo algorithm have their own advantages, which are widely used in various fields of swarm intelligence algorithms. Sensor scheduling problem is an important research direction in sensor network management. In this paper, a multi-sensor scheduling model is established, and an improved particle swarm optimization algorithm is used to solve the model, the simulation flow and an example are given to verify that the improved algorithm is suitable for multi-sensor and multi-target scheduling problem. The simulation results show that the improved algorithm has faster convergence speed and better performance, and is more effective for multi-sensor and multi-target scheduling problem. Future research will also focus on the intelligent scheduling of multi-sensor targets in complex situations.

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