Optimization of Aviation Wireless Sensor Network based on Discrete Cuckoo Search Algorithm

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Abstract. Aiming at the problems of multiple coverage blind areas, poor monitoring quality, and low utilization of sensor network nodes in aviation wireless sensor networks, a discrete cuckoo search (DCS) is proposed, and an objective coverage optimization function is established. Aiming at the fact that the previous cuckoo search is not suitable for discrete values, the binary code conversion formula is used to perform binary code conversion on the jump path of each position update of Levy flight, which makes the algorithm converge faster and avoids the limitations of local search. In the simulation, the discrete cuckoo search was compared with ant colony optimization (ACO) and particle swarm optimization (PSO). Simulation experiment results show that the proposed discrete cuckoo search (DCS) has a great advantage in convergence speed, more targets are detected, and the target coverage in the aerial wireless sensor network is effectively improved.

Key words: Discrete cuckoo search, aviation, wireless sensor networks, coverage optimization

1. Introduction
The wireless sensor network (WSN) is make up of many sensors that can sense and check the external world through wireless communication. It is widely used in environmental monitoring, production safety monitoring, intelligent transportation, medical health, military and other fields [1-2]. WSN has the characteristics of miniaturization, low power consumption, less wiring, easy installation, etc. There are practical problems such as heavy cables, difficult wiring, and poor flexibility in the network, which provide a new method of information acquisition and processing for avionics systems [3-4].

In the aviation field, In the aviation field, the coverage is a key issue in the configuration of WSN. In most cases, a good number of sensor nodes are directly and randomly covered to meet the sensor node's coverage requirements of the target area [5-6]. In view of the special area of the sensor and the limited battery power of the sensor, it is often necessary to randomly deploy sensor nodes in the monitoring area on a large scale, which may lead to partial areas covering blind spots or high-density nodes, and the quality of target detection will be directly affected by detection blind spots[7]. When receiving nodes receive, process and transmit data, high node density wastes energy, and too much redundant data will cause data disturbance and block the channel, affect the reliability of the network, and cause a lot of waste of resources in energy consumption and cost. Therefore, it is necessary to adjust the deployment of sensor nodes to make it more evenly distributed and higher coverage in the detection area, so as to more rationally allocate cyberspace resources and better complete perception and information acquisition tasks, which is of great significance for improving network survivability, improving network reliability, and saving network construction costs.
With the extensive application of intelligent algorithms in optimization, most of the researches have used intelligent algorithms to optimize the coverage of WSN. Literature [8] proposed a WSN based on firefly algorithm (FA) to maximize coverage. Due to the consideration of reducing the moving distance, the coverage of the algorithm still needs to be improved; Literature [9] proposed an optimization method for node deployment based on extrapolated artificial bee colony (EABC), the coverage is improved compared with the original algorithm, but its coverage is still not ideal; Literature [10] proposed a coverage optimization strategy based on the improved grey wolf optimizer (GWO), but did not consider the presence of obstacles in actual deployment; Literature [11] proposed an adaptive chaotic quantum particle swarm optimization algorithm to optimize mobile sensor network coverage. Compared with chaotic quantum particle swarm optimization algorithms and particle swarm optimization, the coverage performance of wireless sensor networks has been more effectively improved. Literature [12] aimed at coverage rate and used improved fish swarm optimization (FSO) to optimize the deployment of sensor nodes, which significantly improved the network coverage area. But only for isomorphic sensors, it does not consider heterogeneous sensors and the monitoring environment in complex situations. Although the above method is effective in deploying uplinks on WSN nodes, in order to meet actual application requirements, the coverage and uniformity of WSN still need to be improved.

Cuckoo Search Algorithm (CSA) is an intelligent optimization algorithm which has emerged in recent years with the advantages of easy implementation, few parameters, and strong search capabilities [13]. CSA is widely used and provides a powerful tool for wireless sensor network coverage optimization technology. To this end, in view of the harsh environment and unmanned monitoring scenarios where traditional aviation sensors are located, and the number and monitoring capabilities are limited, a discrete cuckoo search (DCS) is introduced [14-15]. In this paper, a method for optimizing the placement of sensor nodes in aeronautical wireless sensor networks to improve the target coverage rate is proposed, and the DCS is used to solve the target function, which makes up for the deficiencies of some optimization algorithms and improve the efficiency and accuracy of the optimization solution. The results of simulation and theoretical analysis demonstrate that the proposed discrete cuckoo search can effectively increase the coverage of the target area of the mid-sensor nodes of the aviation WSN. At the same time, compared with ant colony optimization (ACO) and particle swarm optimization (PSO), the discrete cuckoo search has stronger convergence, and the number of monitored targets is more.

2. System model
Due to the limited sensor perception capability, only a limited number of targets within the monitoring range of the sensor node can be covered. The coverage relationship matrix $M$ in formula (1) represents the coverage relationship between $X$ monitored targets and $Y$ sensor nodes in the aeronautical sensor network.

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,N-1} & m_{1,N} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,N-1} & m_{2,N} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ m_{X-1,1} & m_{X-1,2} & \cdots & m_{X-1,Y-1} & m_{X-1,Y} \\ m_{X,1} & m_{X,2} & \cdots & m_{X,Y-1} & m_{X,Y} \end{bmatrix} \quad (m_{x,y} \in \{0,1\})$$

As shown in equation (1), in the coverage relation matrix $M$, $m_{x,y}$ means that the coverage relationship between the $x$-th monitored target and the $y$-th sensor node. When $m_{x,y} = 1$, it means that the $y$-th sensor node can monitor the $x$-th monitored target, or that the $x$-th monitored target is within the coverage of the $y$-th sensor node. However, when the $x$-th monitored target cannot be detected by
the \(y\)-th sensor node, or the \(x\)-th monitored target is not within the coverage of the \(y\)-th sensor node, \(M_{x,y} = 0\).

Also because of the limited monitoring capabilities, not all targets within the coverage area can be monitored. The monitoring matrix \(N\) represents the monitoring relationship of whether the target to be monitored is monitored by the sensor node, such as equation (2).

\[
N = \begin{bmatrix}
    n_{1,1} & n_{1,2} & \cdots & n_{1,Y-1} & n_{1,Y} \\
    n_{2,1} & n_{2,2} & \cdots & n_{2,Y-1} & n_{2,Y} \\
    \vdots & \vdots & \ddots & \vdots & \vdots \\
    n_{X-1,1} & n_{X-1,2} & \cdots & n_{X-1,Y-1} & n_{X-1,Y} \\
    n_{X,1} & n_{X,2} & \cdots & n_{X,Y-1} & n_{X,Y}
\end{bmatrix} \quad (n_{x,y} \in \{0,1\}) \quad (2)
\]

In the monitoring relationship matrix \(N\), \(n_{x,y} = 1\) means that the \(x\)-th monitored target is within the monitoring range of the \(y\)-th sensor node and the \(y\)-th sensor node can monitor the \(x\)-th monitored target. When \(n_{x,y} = 0\) means that the \(x\)-th monitored target cannot be detected by the \(y\)-th sensor node. If the maximum number of monitoring targets in each sensor node within the coverage is \(S\), the constraint condition is as shown in equation (3).

\[
\sum_{x=1}^{X} n_{x,y} \leq S, \quad y = 1 \ldots Y \quad (3)
\]

Suppose a target to be monitored requires at least \(C\) sensor nodes to detect at the same time, and a sensor node monitors at most \(S\) targets simultaneously, the maximum quantity of monitored targets is maximized as the problem optimization target. The mathematical model of the problem is represented by formula (4)-(6).

Objective: \(\max f(n_{11}, n_{12}, \ldots, n_{XY}) = \sum_{x=1}^{X} w_x\)

among them \(w_x = \begin{cases}
1 & \sum_{y=1}^{Y} n_{x,y} \geq C \\
0 & \sum_{y=1}^{Y} n_{x,y} < C
\end{cases} \quad (4)
\]

Subject to:

\[
\sum_{x=1}^{X} n_{x,y} \leq S, \quad y = 1 \ldots Y \quad (5)
\]

\[
n_{x,y} \leq m_{x,y} \quad (6)
\]

In equation (5), the objective function is expressed as the total amount of monitored targets. If the \(x\)-th target can be successfully detected, it is represented by \(w_x = 1\), but when \(w_x = 0\), it means that the target cannot be successfully detected. Constraint 1 in equation (5) indicates that the monitoring capability of the sensor node is limited and constraint 2 indicates that the monitored target that can be monitored by the sensor node must be within the sensor coverage.
3. Target coverage of aerial wireless sensor networks based on discrete cuckoo search

3.1. Description of cuckoo search algorithm
Cuckoo search algorithm (CSA) is by imitating the cuckoo breeding and special way flight evolved. In nature, cuckoos generally do not have the ability to hatch, and usually lays eggs in other foster birds' nests for hatching. If host bird discovers the cuckoo's behavior, the host bird will directly throw the cuckoo's eggs out of the nest, or gives up the current nest, and choose a new location to build the nest. In order to avoid this, cuckoos generally choose to lay eggs in the nest where the nest bird has just laid eggs, which is not easy to be found by the host bird, thereby reducing the possibility of the host bird moving out of the nest. At the same time, the cuckoo will remove one or more eggs of the host, so as not to be found by the host to increase the number of eggs, but also reduce the competition of the host's juvenile dimension. Once the cuckoo's eggs are preserved, they usually hatch before the host bird's eggs. These new larvae will instinctively push the eggs of the host birds that have not hatched out of the nest to ensure that the host bird can raise the cuckoo larvae.

The CSA is to simulate the cuckoo's behavior of continually looking for a suitable horse's nest to lay his eggs in order to breed offspring, so as not to be discovered by the host, but to be hatched and raised into an adult. Random search, comparison, and judgment can finally solve the optimization problem. The cuckoo algorithm presupposes the following three assumptions: (1) Each cuckoo randomly selects a nest for spawning each time, and can only lay one egg at a time. (2) Keep the best nest for future use. (3) Make sure the amount of offered bird's nest is unchanged, and host may find cuckoo eggs and cause hatching failure. There are two basic search methods for the cuckoo algorithm: one is to use Levy Flight to randomly swim to discover a suitable bird's nest, and second is to discover a brand-new bird's nest location by random drift after deviations are discovered. The specific actions are usually below:

Step 1: Let the maximum amount of iterations be T, the population size be G, and the probability of discovery be p. The bird's nest is initialized randomly, which is the initial solution of the optimization problem.

Step 2: According to the fitness function, evaluate the fitness of the initial bird nest and retain the best quality nest.

Step 3: Follow the Levy Flight random search method to look for the bird's nest position. Use the fitness function to calculate the updated bird's nest quality and compare it with the look for bird's nest quality. Replace poorer bird nests with better ones. The update formula of bird's nest position is (7).

\[ X_{k+1}^i = x_i^k + \alpha \otimes L(\lambda) \]  \hspace{1cm} (7)

In equation (7): \(X_i^k\) and \(X_{k+1}^i\) are the location of the \(i\)-th bird's nest in the \(k\)-th and \(k+1\) iterations respectively; \(\otimes\) is point-to-point multiplication; \(\alpha\) is the step size control parameter; \(L(\lambda)\) is the search path, \(L(\lambda) \sim u = t^{-\lambda} \).

Step 4: Generate a random number \(r\) and compare it with the discovery probability \(P_d\). If \(r > P_d\), the selected bird's nest position is discarded, then use the random walk search method to find the new bird's nest location. The bird's nest position is updated by formula (8).

\[ X_{k+1}^i = X_k^i + r \times (X_j^k - x_i^k) \]  \hspace{1cm} (8)

In equation (8): \(r\) is the scaling factor, \(r \in [0,1]\); \(X_j^k\) is the bird's nest near \(X_i^k\).

Step 5: Compare the improved bird's nest with the previous best bird's nest, and keep bird's nest with better quality.

Step 6: Perform steps 3 to 5 until the previously set number of iterations is completed, and the best quality bird nest is output.

3.2. Discrete cuckoo search algorithm
CSA is a new type of natural element-based heuristic algorithm proposed by British scholars Yang and
Deb on the basis of swarm intelligence technology in 2009. CSA has strong global search ability, few selection parameters and strong robustness. But the original cuckoo search algorithm is only appropriate for resolving continuous values, not for discrete values. Ouyang et al. proposed a discrete cuckoo search (DCS) in order to resolve discrete problems.

The DCS requires a binary code transformation of the jump path for each position update of Levy flight. The transformation formula of the binary coding is as follows:

\[
\begin{align*}
\text{If } & \text{ rand}() \leq p_r \\
\text{Sig}(\text{Levy}) &= \frac{1}{1 + \exp(-\text{Levy})} \\
\text{w}_{x}^{g+1} &= \begin{cases} 
1 & \text{rand} \leq \text{Sig}(\text{Levy}) \\
0 & \text{otherwise}
\end{cases}
\end{align*}
\]

Else

\[
\begin{align*}
\text{If } & \text{ Levy} \leq 0 \\
\text{Sig}(\text{Levy}) = 1 - \frac{2}{1 + \exp(-\text{Levy})} \\
\text{w}_{x}^{g+1} &= \begin{cases} 
0 & \text{rand} \leq \text{Sig}(\text{Levy}) \\
\text{w}_{x}^{g} & \text{otherwise}
\end{cases}
\end{align*}
\]

Else

\[
\begin{align*}
\text{Sig}(\text{Step}) = \frac{2}{1 + \exp(-\text{Step})} - 1 \\
\text{w}_{x}^{g+1} &= \begin{cases} 
1 & \text{rand} \leq \text{Sig}(\text{Step}) \\
\text{w}_{x}^{g} & \text{otherwise}
\end{cases}
\end{align*}
\]

End If

Where rand is the generated random number; \( p_r \) is the binary coded control parameter and satisfies \( p_r \in [0,1] \). The larger \( p_r \), the stronger the global diversity of the discrete cuckoo algorithm; the smaller \( p_r \), the stronger the convergence of the discrete cuckoo algorithm.

4. Simulation

In the experiment, set the monitoring range to \( 500 \times 500 \), the target to be monitored is 200, and the positions of the sensor nodes and the target to be monitored are randomly distributed. Within the coverage area, each sensor node can monitor up to 4 targets, and the number of sensor nodes that need to be monitored at least for each target to be monitored is 3 at the same time.

Set cuckoo algorithm parameters: population number \( N = 40 \), maximum evolution number \( T = 100 \), and initial probability of discovery \( p_r = 0.25 \). To be able to prove the effect of the algorithm, DCS, PSO and ACO were used to optimize the target coverage method of the WSN with the same parameters, then the target coverage rate of the three algorithms was obtained.

Figure 1 shows the target coverage rate when the number of sensor nodes is 200 and the sensor sensing radius is set to 60 meters and 80 meters respectively. In Figure 1, (a) is a perception radius of 60 meters, and (b) is a perception radius of 80 meters. It can be seen from Figure 1 that the DCS has faster convergence speed and successfully avoids the phenomenon of evolutionary stagnation. Under different radii, DCS improved the target coverage rate better than PSO and ACO. The target coverage rates reached 82% and 95% when the radii were 60 meters and 80 meters, respectively.
Figure 1. The change of target coverage rate with the number of algorithm iterations

Figure 2 is a line chart of the number of targets monitored by the sensor node. In Figure 2, the number of sensor nodes is 200 and the sensor sensing radius is set to 60 meters and 80 meters respectively. It can be seen from the simulation result graph that as the amount of sensor nodes raises, the number of detected targets also increases. Compared with the two algorithms of PSO and ACO, the number of targets monitored by DCS has obvious advantages.

Figure 2. The number of successfully detected targets changes with the number of algorithm iterations

5. Conclusion
Aiming at the problems of limited monitoring capability, large redundancy, short life span, and high cost of the detection process in the traditional aviation wireless sensor network, a discrete cuckoo search is proposed. In the simulation and experiment, the DCS is compared with PSO and ACO. The outcomes demonstrate that the proposed discrete cuckoo search algorithm offers faster convergence speed and stronger global search capabilities, which can effectively increase the target coverage of aviation wireless sensor networks.

Acknowledgments
This paper is supported by the project of Youth and Middle-aged Scientific and Technological Innovation Leading Talents Program of the Corps (No. 2018CB006), the Major scientific and technological projects of the Corps (2017AA005-04), the project of Promoting Scientific Research Cooperation and High-level Personnel Training with Americas and Oceania. The corresponding author is Jie Zhou.
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