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Optimized deployment of a radar network based on an improved firefly algorithm

Key words: Improved firefly algorithm; Radar surveillance network; Deployment optimization; Unmanned aerial vehicle (UAV) invasion defense

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Motivation

1. To form a tight and reliable radar surveillance network with limited resources, it is essential to investigate optimized radar network deployment.

2. This optimization problem is difficult to solve due to its nonlinear features and strong coupling of multiple constraints.

3. Most of previous works built a simple deployment model with only one type of radar and one height detection level, and the applied optimization algorithms, such as GA and ant colony algorithms, have poor performance when it comes to generating a suitable deployment solution in complicated scenarios.

Main idea

1. To address these issues, we build a more complicated model with multiple radar types and multiple height-detection levels.

2. The firefly algorithm (FA) is a new swarm intelligence optimization algorithm.

3. We propose an improved firefly algorithm (IFA) to generate satisfactory solutions.

4. Experiments have been conducted on 12 famous benchmark functions and in a classical radar deployment scenario.

Method

Our proposed IFA employs three strategies:

1. Position initialization of fireflies in a chaotic sequence.

2. A neighborhood learning strategy with a feedback mechanism.

3. A chaotic local search by elite fireflies.

These strategies aim to obtain a trade-off between exploration and exploitation abilities.

Optimization model

(1) Airspace-covering coefficient

$$\rho_k = \frac{\bigcup_{i=1}^{L} \left(A_{ik} \cap A\right)}{A}, \qquad (1)$$

(2) Airspace-overlap coefficient

$$\mu_k = \frac{\left(\bigcup_{i,j=1}^{L} \left(A_{ik} \cap A_{jk}\right)\right) \cap A}{A}, \qquad (3)$$

(3) Objective function

$$\begin{aligned} \max F &= \lambda_1 \rho + \lambda_2 \mu \\ &= \lambda_1 \sum_{k=1}^{M} \omega_k \rho_k + \lambda_2 \sum_{k=1}^{M} \omega_k \mu_k, \end{aligned} \qquad (5)$$

$$\lambda_1 + \lambda_2 = 1$$

(4) Constraints

$$\begin{cases} \rho_0 > \rho_1, \\ \tau = 1 - \dfrac{\left(\bigcup\limits_{\substack{i,j,l,t=1,\\ i\neq j\neq l\neq t}}^{L} \left(A_{0i} \cap A_{0j} \cap A_{0l} \cap A_{0t}\right)\right) \cap A}{A} \geq \tau_1. \end{cases} \qquad (6)$$

IFA algorithm

Algorithm 2 Proposed improved firefly algorithm

Require: objective function $f(x)$, $x = (x_1, x_2, \ldots, x_D)$
Initialize the population of fireflies X_i $(i = 1, 2, \ldots, N)$ with chaotic sequence
while FE<MAX_FEs **do**
  for $i = 1$ to N **do**
    for $j = 1$ to N **do**
      if $f(X_i) < f(X_j)$ **then**
        Move firefly X_i towards X_j according to Eq. (9)
      end if
    end for
  end for
  /* Neighborhood learning strategy with feedback */
  /* mechanism */
  for $i = 1$ to N **do**
    if $r < p_n$ **then**
      Move firefly X_i with neighborhood learning strategy
      FE++
    end if
  end for
  /* Elite fireflies' chaotic local search */
  Select p_e of best fireflies as an elite group E
  for $i = 1$ in E **do**
    Apply chaotic search to firefly X_i
    Replace X_i with the best solution of chaotic local search
    FE++
  end for
  Calculate the light intensity in the new place
  FE++
end while

Major results

1. Algorithm performance on benchmark functions

Table 3 Experimental results of the mean value on benchmarks

Function	Mean value					
	Classical FA	Standard FA	WSSFA	CFA	NSRaFA	Our proposed IFA
f_1	6.87e + 04	6.89e − 03	7.11e + 04	3.07e + 04	8.55e − 91	**0.00e + 00**
f_2	1.72e + 03	2.31e + 00	3.31e + 05	8.67e + 10	4.56e − 47	**0.00e + 00**
f_3	1.51e + 05	3.63e + 03	1.58e + 05	8.45e + 04	6.49e − 89	**0.00e + 00**
f_4	8.40e + 01	6.76e + 00	8.74e + 01	6.78e + 01	2.90e − 46	**0.00e + 00**
f_5	1.79e + 08	6.07e + 02	2.79e + 08	6.61e + 07	2.89e + 01	**4.87e − 09**
f_6	1.25e + 03	6.20e + 00	1.19e + 03	8.09e + 02	**0.00e + 00**	**0.00e + 00**
f_7	3.01e + 01	4.13e − 01	3.82e + 01	2.72e + 01	6.44e − 02	**5.32e − 02**
f_8	−1.94e + 03	−6.32e + 03	−1.98e + 03	−2.38e + 03	**−9.21e + 03**	−5.46e + 03
f_9	2.95e + 02	5.50e + 01	3.40e + 02	3.53e + 02	**0.00e + 00**	**0.00e + 00**
f_{10}	2.00e + 01	7.21e − 01	2.04e + 01	1.88e + 01	**4.44e − 16**	**4.44e − 16**
f_{11}	6.31e + 02	2.25e − 02	6.25e + 02	2.82e + 02	**0.00e + 00**	**0.00e + 00**
f_{12}	4.51e + 08	1.33e + 00	6.35e + 08	1.26e + 08	6.92e − 01	**1.31e − 03**
$w/t/l$	12/0/0	12/0/0	12/0/0	12/0/0	7/4/1	–

Boldface indicates the best results among the algorithms

Major results

1. Algorithm performance on benchmark functions

Table 4 Experimental results of the standard deviation value on benchmarks

Function	Standard deviation value					
	Classical FA	Standard FA	WSSFA	CFA	NSRaFA	Our proposed IFA
f_1	6.66e + 03	5.68e − 03	6.83e + 03	1.42e + 04	4.60e − 90	**0.00e+00**
f_2	6.97e + 03	1.63e + 00	5.75e + 05	4.62e + 11	2.46e − 46	**0.00e + 00**
f_3	3.96e + 04	1.67e + 03	6.05e + 04	5.59e + 04	3.49e − 88	**0.00e + 00**
f_4	1.40e + 00	2.84e + 00	3.90e + 00	1.02e + 01	1.56e − 45	**0.00e + 00**
f_5	1.75e + 07	1.16e + 03	3.91e + 07	5.86e + 07	5.56e − 02	**2.61e − 08**
f_6	5.39e + 01	6.20e + 00	5.35e + 01	2.23e + 02	**0.00e + 00**	**0.00e + 00**
f_7	6.83e + 00	1.43e − 01	2.11e + 01	2.23e + 01	4.89e − 02	**3.95e − 02**
f_8	4.74e + 02	1.13e + 03	4.63e + 02	5.04e + 02	**5.35e + 02**	8.87e + 02
f_9	1.10e + 01	1.61e + 01	1.13e + 01	4.03e + 01	**0.00e + 00**	**0.00e + 00**
f_{10}	1.09e − 01	5.29e − 01	7.32e − 02	9.53e − 01	**0.00e + 00**	**0.00e + 00**
f_{11}	7.81e + 01	2.43e − 02	7.77e + 01	1.22e + 02	**0.00e + 00**	**0.00e + 00**
f_{12}	6.98e + 07	8.93e − 01	1.19e + 08	1.62e + 08	2.26e − 01	**2.62e − 03**
$w/t/l$	12/0/0	12/0/0	12/0/0	12/0/0	7/4/1	–

Boldface indicates the best results among the algorithms

Major results

2. IFA for deployment optimization of the radar network

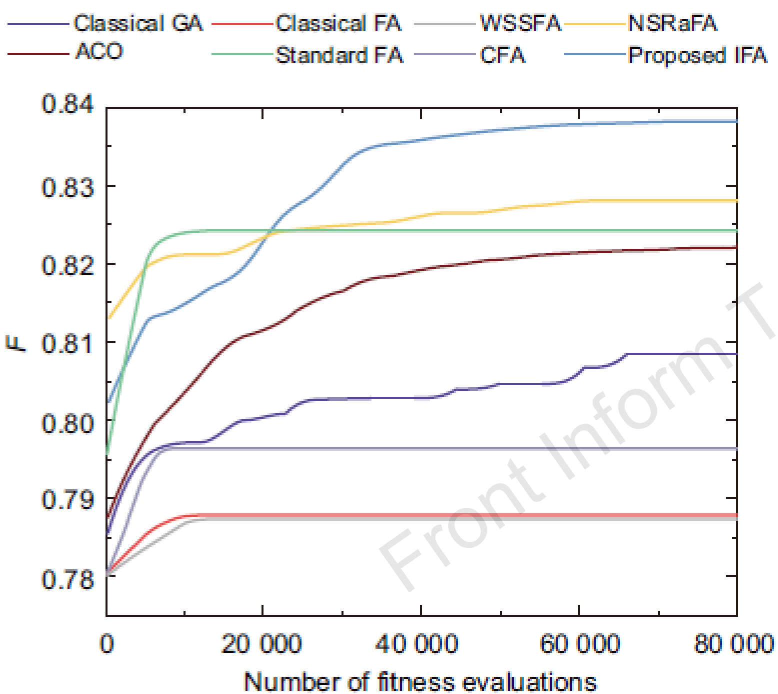

Fig. 5 Average evolution curves under different algorithms. References to color refer to the online version of this figure

Table 6 Results of different algorithms

Algorithm	F Mean	F Maximum	F Minimum	F Variance
Classical GA	0.8085	0.8216	0.8070	1.7636e − 05
ACO	0.8220	0.8245	0.8067	2.6027e − 05
Classical FA	0.7879	0.8012	0.7776	2.9275e − 05
Standard FA	0.8243	0.8272	0.8106	1.2849e − 05
WSSFA	0.7874	0.8005	0.7788	2.7269e − 05
CFA	0.7964	0.8137	0.7819	3.3682e − 05
NSRaFA	0.8281	0.8304	0.8242	8.0651e − 06
Proposed IFA	**0.8380**	**0.8392**	**0.8355**	**5.9443e − 06**

F: comprehensive detection performance of the surveillance network. Boldface indicates the best results among the algorithms

Major results

2. IFA for deployment optimization of the radar network

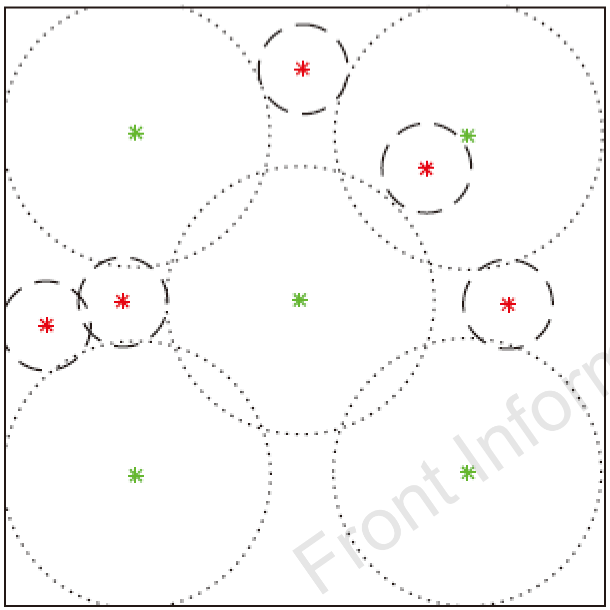

Fig. 6 Radar detection scope at the height of 500 m. Red dots: locations of type-A radars; green dots: locations of type-B radars; solid circles: detection ranges of type-A radars; dotted circles: detection ranges of type-B radars. References to color refer to the online version of this figure

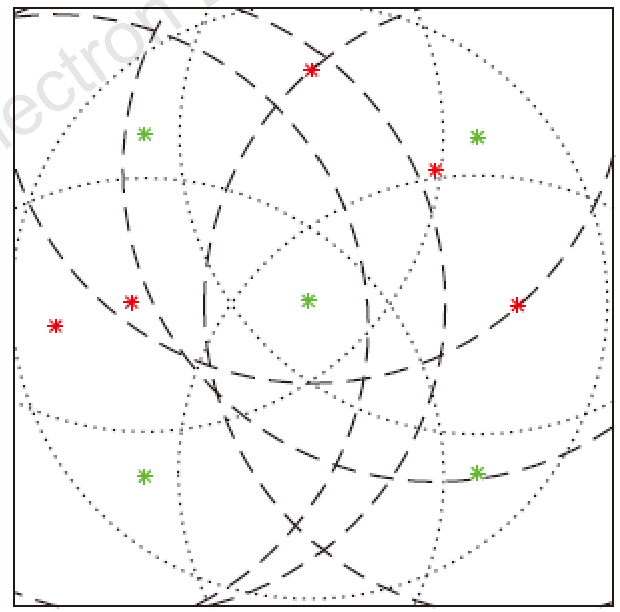

Fig. 7 Radar detection scope at the height of 3000 m. Red dots: locations of type-A radars; green dots: locations of type-B radars; solid circles: detection ranges of type-A radars; dotted circles: detection ranges of type-B radars. References to color refer to the online version of this figure

Conclusions

1. A more complicated radar deployment optimization model with multiple radar types and multiple height detection levels has been described.

2. An improved firefly algorithm has been proposed. It employs three strategies: (1) position initialization of fireflies in a chaotic sequence; (2) a neighborhood learning strategy with a feedback mechanism; (3) chaotic local search by elite fireflies.

3. Our IFA achieves a good trade-off between exploration and exploitation and has much better performance than the classical FA and the four recently proposed FA variants.