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Research on Intelligent Minefield Attack Decision Based on Adaptive Fireworks Algorithm

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Abstract

The decision of intelligent minefield attacking tank forces is a complex multi-constraint and multi-objective nonlinear optimization problem. Aiming at the common defects of commonly used intelligent algorithms and combining with the characteristics of fireworks algorithm, this paper proposed an adaptive fireworks algorithm to deal with it. In this paper, we first established the mathematical model of this problem and transformed the model into an unconstrained single-objective extremum by using the external penalty function method. Furthermore, the adaptive fireworks algorithm is used to solve the model. In order to verify the superiority of adaptive fireworks algorithm to deal with this problem, experimental results show that the adaptive fireworks algorithm has faster convergence speed and shorter computation time than the other algorithms, and the results can intuitively describe the reasonable task allocation scheme of the complex situation, which provides a foundation for studying the force control.

Keywords Intelligent minefield · External penalty function method · Fireworks algorithm · Multi-constrained and multi-objective optimization

1 Introduction

At present, the fourth-generation intelligent minefield system which is characterized by network and intelligence is an inevitable trend of modern battlefield development, and it is also the focus of the research on the landmine system of all the world's military powers [1]. That the attack decision planning of the minefield system composed of multiple intelligent mines is the key to fully exploiting the advantages of multi-intelligent mine cooperative combat, thus making the task complexity and intelligent minefield ability to be well coordinated. The weapon–target assignment problem (WTA) is a complex multi-constrained and multi-objective nonlinear optimization problem.

To solve the aforementioned problem, some scholars have done research with traditional classical theory, such as game theory [2] and dynamic programming [3]. However, it is facing challenges of algorithm model complexity, massive computation load and poor real-time performance. With the development of intelligent heuristic computing technology, intelligent optimization algorithm has been widely used in the weapon target assignment problem which provides a new idea. Improved genetic and ant colony optimization algorithm [4,5], fuzzy genetic algorithm [6], immunity based on ant colony optimization algorithm [7], improved artificial immune algorithm [8], compact genetic algorithm [9], improved auction algorithm [10] and evaluation of several fusion algorithms [11] showed good performance in solving this problem. However, these intelligent algorithms generally have the drawback of being easy to fall into local optimum, needing to be improved.

The fireworks algorithm was first proposed by Professor Tan Yin in 2010. And because of its strong operational parallelism and population diversity, it stands out of many intelligent algorithms, so that it drew widespread attention of scholars. Firstly, based on characteristics of the intelligent minefield attack decision problem, the mathematical model of intelligent minefield attacking tanks decision is established. The penalty function method was used to turn the multi-constrained and multi-objective nonlinear optimization problem into an unconstrained single-objective nonlinear programming problem, and then the improved fireworks algorithm (adaptive fireworks algorithm) was applied

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to deal with the planning problem; finally, this method is adopted to verify the simulation and analysis based on the concrete example data. In order to verify the superiority of adaptive fireworks algorithm to deal with this problem, we respectively use the basic fireworks algorithm (FWA), adaptive fireworks algorithm (AFWA), multi-intelligence improved glowworm swarm optimization (MIGSO), simulated annealing-discrete particle swarm hybrid optimization algorithm (SA-DPSO) and multi-intelligence genetic algorithm(MIGA) to do simulation calculation.

2 Mathematical Model of Intelligent Minefield Attack Tanks Decision

Decision-making process of intelligent minefield attacking on the enemy tank forces is to develop the attack allocation plan of each intelligent mine to tank target for maximizing the effectiveness of intelligent minefield combat effectiveness. Aiming at this problem, the mathematical models **[1/11]** of decision variables, objective functions and constraints are designed, respectively, firstly, and then the external penalty function method was used to transform the model into unconstrained single-objective nonlinear programming problem.

2.1 Design Decision Variables

Noted the number of intelligent mines as N and the target number of being attacked tanks as M. Image that intelligent mine W_i (i=1,2,…,N) can carry B_i submunition at most, thus as for the entire minefield, the total submunition quantity of B can be expressed as follows:

$$B = \sum_{i=1}^{N} B_i. \tag{1}$$

Decision variables can be designed as the submunition number of a certain intelligent mine for assigning to a tank target, which is X_{mj}: The mth submunition is assigned to tank T_j, which is an integer of 0-1, $m = 1, \ldots, B$; $j = 1, \ldots, M$.

The geographic north direction is the zero-angle direction, and the clockwise direction is the positive direction of the angle. Assume that intelligent minefields are equipped with$N$ intelligent mines and the offensive forces are equipped with M tanks. The confrontation situation map between intelligent mines and tanks is shown in Fig. 1. The warhead direction angle of the intelligent mine W_i is $a_i (0 \leq \alpha_\iota \leq 2\pi)$. Assume that the exiting velocity of submunitions is v_0, and the elevation angle with the horizontal plane is γ_0 $(0 \leq \gamma_0 \leq \pi/2)$. The velocity of the tank T_j (j=1, 2,…,M) is v_j, and the motion direction is $\beta_j (0 \leq \beta_j \leq 2\pi)$.

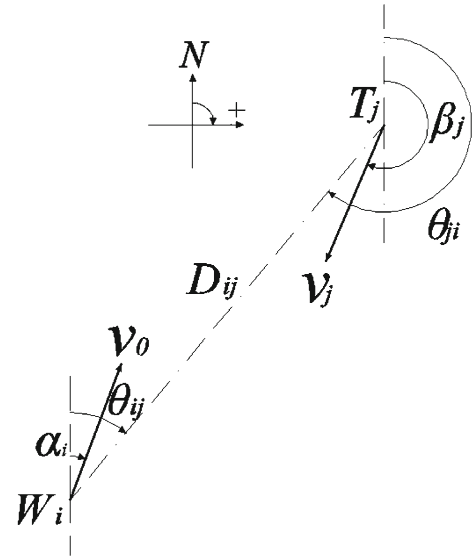

Fig. 1 Confrontation situation map between intelligent mines and tanks

Marking the distance between the mine W_i and the tank T_j D_{ij} and the azimuth angle of the tank T_j relative to the mine W_i is $\theta_{ij} (0 \leq \theta_{ij} \leq 2\pi)$, then the direction angle of the mine W_i relative to the tank T_j is $\theta_{ji} (0 \leq \theta_{ji} \leq 2\pi)$, and the relationship can be expressed as:

$$\theta_{ji} = \begin{cases} \theta_{ij} + \pi & \theta_{ij} \leq \pi \\ \theta_{ij} - \pi & \theta_{ij} > \pi \end{cases}. \tag{2}$$

Intelligent minefield attack decisions need to take it into account the distance between mines and tanks, the angle relations and speed. The following three aspects of the threat factors were defined as follows.

2.2 Design Objective Function

(1) Distance threat factor definition
Marking the intelligent mines detection radius of the sensor R_s^W and the effective submarine mine attack distance R_a^W, then the threat factors TH_{ij}^D between the intelligent mine W_i and the tank T_j can be expressed as:

$$TH_{ij}^D = \begin{cases} 1 & D_{ij} \leq R_a^W \\ 1 - \frac{D_{ij} - R_a^W}{R_s^W - R_a^W} & R_a^W < D_{ij} \leq R_s^W \\ 0 & D_{ij} > R_s^W \end{cases}. \tag{3}$$

(2) Angle threat factor definition
The angle threat factor of the intelligent mine to the tank is related to the heading angle of the landmine warhead and the azimuth angle of the tank relative to the mine. $\Delta\alpha_\iota (0 \leq \Delta\alpha_\iota \leq \pi)$ is the angle between the warhead direction angle α_i of the intelligent mine W_i and the azimuth angle θ_{ij} of the

tank T_j relative to the mine W_i, then $\Delta\alpha_i$ can be expressed as:

$$\Delta\alpha_i = \begin{cases} \left|\alpha_i - \theta_{ij}\right| & \left|\alpha_i - \theta_{ij}\right| \le \pi \\ 2\pi - \left|\alpha_i - \theta_{ij}\right| & \left|\alpha_i - \theta_{ij}\right| > \pi \end{cases}. \tag{4}$$

Thus, the angle threat factor of intelligent mine W_i to tank T_j can be further defined as:

$$TH_{ij}^{\alpha} = 1 - \left(\frac{\Delta\alpha_i}{\pi}\right)^2. \tag{5}$$

(3)Speed threat factor definition

The speed threat factor of an intelligent mine to a tank is related to the speed of tank and the exit speed of submarine. Obviously, the faster the tank moves, the harder it hits; however, the faster the exit speed of submunitions is, the more conducive. It is to ensure the hit rate of the tank. Here, we defined speed threat factor of the intelligent mine W_i to the tank T_j as:

$$TH_{ij}^{v} = \begin{cases} 1 & \frac{v_j}{v_0 \cos\gamma_0} < 0.5 \\ 1.45 - 0.9\frac{v_j}{v_0 \cos\gamma_0} & 0.5 \le \frac{v_j}{v_0 \cos\gamma_0} < 1.5 \\ 0.1 & \frac{v_j}{v_0 \cos\gamma_0} \ge 1.5 \end{cases}. \tag{6}$$

Intelligent minefield attack decision needs to integrate the above three threats, so the threat index of the intelligent mine W_i to the tank T_j can be expressed as:

$$TH_{ij} = \omega_1 \cdot TH_{ij}^{D} + \omega_2 \cdot TH_{ij}^{\alpha} + \omega_3 \cdot TH_{ij}^{v}, \tag{7}$$

where $\omega_k (k = 1, 2, 3)$ is a nonnegative weighting coefficient. We first use the analytic hierarchy process(AHP) to solve the weight of each index and then use the gray correlation method to test whether the weights are properly allocated. If the importance of the gray correlation method is not consistent with that obtained by the AHP, then the AHP process is repeated until the agreement is reached. The calculation method is referred to [16],

where $\sum_{k=1}^{3} \omega_k = 1$.

Each landmine in a minefield can carry multiple submunitions, and an intelligent mine attacks an enemy target through submunitions. In other words, each intelligent mine can attack multiple targets with multiple submunitions, but each sub-ammunition can attack only one target.

Assuming that the mth sub-ammunition is assigned to the tank T_j, the threat index of the sub-ammunition m to the tank T_j can be expressed as TH_{mj}, and the survival probability of tank T_j after being attacked can be expressed as (1-TH_{mj}). Therefore, the survival probability SV_j of tank T_j after a coordinated attacking of smart minefield can be expressed as:

$$SV_j = \prod_{m=1}^{B} (1 - TH_{mj})^{Xmj}, \tag{8}$$

where X_{mj} takes the value 0 or 1, and X_{mj} = 1 means that the mth sub-ammunition is assigned to tank T_j.

The objective function of intelligent minefield attack decision optimization can be expressed as:

$$\min \quad E(s) = \sum_{j=1}^{M} \sum_{i=1}^{N} \{TH_{ji} \cdot SV_j\}, \tag{9}$$

where $E\ (s)$ is the sum of the threat exponents for the entire intelligent minefield after attacking enemy tanks.

2.3 Design Constraints

(1) A sub-ammunition can only attack a tank, then:

$$\sum_{j=1}^{M} X_{mj} = 1 \quad (m \in G). \tag{10}$$

The total set of available submunitions is G, which is denoted as $G = \{m, m = 1,2, \ldots, B\}$.

(2) A tank can be attacked by up to C submunitions at most. If C submunitions still failed to destroy the target, then they gave up attacking the target continuously. C is a positive integer, then:

$$\sum_{m=1}^{B} X_{mj} = C \quad (j = 1, 2, \ldots, M). \tag{11}$$

2.4 External Penalty Function Method

The basic idea of the external penalty function method is to use the constraint function in the problem to make the appropriate penalty function [13], thus construct the augmented objective function with parameters for transforming the problem into an unconstrained single-objective nonlinear programming problem.

Consider the problem:

$$\begin{array}{ll} \min & f(x) \\ s.t. & \begin{cases} g_i(x) \le 0, i = 1, \ldots, r, \\ h_j(x) \ge 0, j = 1, \ldots, s, \\ k_m(x) = 0, m = 1, \ldots, t \end{cases}. \end{array} \tag{12}$$

Take a sufficiently large number M >0 and then construct the following function:

$$P(x, M) = f(x) + M\sum_{i=1}^{r}\max(g_i(x), 0) - M\sum_{j=1}^{s}\min(h_j(x), 0) + M\sum_{m=1}^{t}|k_m(x)|. \quad (13)$$

The optimal solution x of the unconstrained extreme value problem min $P(x, M)$ with the augmented objective function $P(x, M)$ as an objective function is also the optimal solution of the original problem.

Therefore, the complex mathematical model can be transformed into the following unconstrained extreme value problem:

$$\min \quad P(x, M) = E(s) + M\sum_{j=1}^{M}\left|\sum_{m=1}^{B}X_{mj} - C\right| + M\sum_{m=1}^{B}\left|\sum_{j=1}^{M}X_{mj} - 1\right|. \quad (14)$$

3 Adaptive Fireworks Algorithm

Fireworks algorithm is a new swarm intelligent algorithm, which has the self-adjusting mechanism with local search ability and global search ability. The explosion radius and the number of explosion spark are different. The explosion radius of the fireworks with poor fitness value is larger, which makes it greater exploration ability (exploration property). The explosion radius of fireworks with good fitness value is smaller, which makes it a greater digging ability (mining property) around the position. In addition, the introduction of Gaussian variation sparks can further increase the diversity of the population [12].

Based on the shortcomings and performance deficiencies of each operator of the basic fireworks algorithm, the enhanced fireworks algorithm puts forward the corresponding improvement strategies and methods. Based on the enhanced fireworks algorithm, the adaptive fireworks algorithm proposed an adaptive explosion radius mechanism, in which the distance between the optimal fireworks in a fireworks group and a selected individual is used as the explosion radius.

3.1 Basic Fireworks Algorithm

The basic principle of the fireworks algorithm is that if the fireworks corresponding fitness function value is smaller, then the number of fireworks explosion spark is larger and the explosion amplitude is smaller. Conversely, the number of fireworks explosion sparks is smaller and the explosion amplitude is greater. Fireworks algorithm consists of four parts [12]: explosion operator, mutation operator, mapping rule and selection strategy.

(1) Explosion operator

a. Explosion intensity

In the fireworks algorithm, the number of sparks generated is as follows:

$$S_i = m\frac{Y_{\max} - f(x_i) + \varepsilon}{\sum_{i=1}^{N}(Y_{\max} - f(x_i)) + \varepsilon}, \quad (15)$$

where S_i is the number of sparks generated by the ith fireworks; m is a constant used to limit the total number of sparks generated; Y_{max} is the adaptive value of the worst individual in the current population; $f(x_i)$ is the fitness value of individual x_i; ε is an extreme small constant used to avoid the denominator becoming zero.

To limit the number of fireworks explosion sparks being too large or too small, we set the following restrictive formulas for calculating the number of sparks generated of each firework:

$$\hat{s}_i = \begin{cases} round(am), & S < am \\ round(bm), & S > bm, \quad a < b < 1 \\ round(S_i), & otherwise \end{cases}, \quad (16)$$

where $\hat{s}_i$ is the number of sparks that the ith firework can produce; *round*() is the rounding function; a and b are given constants.

b. Explosion amplitude

The formula for calculating the range of fireworks explosion amplitude is:

$$A_i = A^*\frac{f(x_i) - Y_{\min} + \varepsilon}{\sum_{i=1}^{N}(f(x_i) - Y_{\min}) + \varepsilon}, \quad (17)$$

where A_i is the explosion amplitude range of the ith fireworks. The explosion spark will randomly move within this range, but can't go beyond this range; A^* is a constant indicating the maximum explosion amplitude; the parameter Y_{min} is the fitness value of the best individual in the current population; the meaning of $f(x_i)$ and parameter ε is the same as that in (15).

c. Moving operation

The moving operation is to move each dimension of the fireworks:

$$\Delta x_i^k = x_i^k + rand(0, A_i), \quad (18)$$

where *rand* (0, A_i) represents a uniform random number generated within the amplitude A_i.

(2) Mutation operator

x_i^k indicates the position of the *n*th individual in the *k*th dimension, and the calculation method of Gaussian variation at the time is expressed as follows:

$$x_i^k = x_i^k \times g, \tag{19}$$

where g is a Gaussian random number which the mean value is 1 and the variance is 1.

(3) Mapping rule

Here, the modular computing mapping rules are used, and the formula is expressed as follows:

$$x_i^k = x_{\min}^k + \left| x_i^k \right| \%(x_{\max}^k - x_{\min}^k), \tag{20}$$

where x_i^k denotes the position of the ith individual beyond the boundary in the kth dimension; x_{max}^k and x_{min}^k, respectively, represent the upper and lower bounds on the boundary of the k dimension; % represents a modular operation.

(4) Selection strategy

In the fireworks algorithm, the Euclidean distance is used to measure the distance between any two individuals:

$$R(x_i) = \sum_{j=1}^{K} d(x_i, x_j) = \sum_{j=1}^{K} \left\| x_i - x_j \right\|, \tag{21}$$

where d (x_i, x_j) represents the Euclidean distance between any two individuals x_i and x_j; R (x_i) denotes the sum of the distance between x_i and other individuals; $j \in K$ means that the jth position belongs to the set K which is the position set of the sparks produced by the explosion operator and the Gaussian mutation.

Use the roulette method for individual choosing. The probability of everyone being selected is denoted by p (x_i):

$$p(x_i) = \frac{R(x_i)}{\sum_{j \in K} R(x_j)}. \tag{22}$$

It can be seen from the above formula, individuals which farther away from the other individuals will have more opportunities to become the next generation of individuals. This selection method ensured the population diversity of the fireworks algorithm.

3.2 Enhanced Fireworks Algorithm

Enhanced fireworks algorithm proposed the corresponding improvement strategies and methods basing on the defects and insufficient performance of the various operators in the basic fireworks algorithm.

(1) Minimum explosion radius detection strategy

In the basic fireworks algorithm, by setting different explosive radius of different fireworks in the population to keep the balance of global search and local search, the population has a balanced exploration and digging ability. However, as for the solution X_k with the lowest fitness value in the fireworks population, the calculated explosion radius will be very small, which leads to the fireworks with the lowest fitness value (the optimal fireworks in the current population) do not play the role of digging in the actual optimization search process due to the excessively small explosion radius.

To avoid this defect, the minimum explosion radius detection strategy [14] is introduced in the enhanced fireworks algorithm. $A_{min,k}$ is the detection threshold with the lowest explosion radius at the kth dimension:

$$A_{ik} = \begin{cases} A_{min,k}, & A_{i,k} < A_{min,k} \\ A_{ik}, & otherwise \end{cases}, \tag{23}$$

where A_{ij} denotes the explosion radius of the fireworks i on the kth dimension. In the selection of $A_{min,k}$, the nonlinear decreasing explosive radius detection strategy is adopted.

$$A_{\min,k}(t) = A_{\text{init}} - \frac{A_{\text{init}} - A_{\text{final}}}{evals_{\max}} \sqrt{(2evals_{\max} - t)t} \tag{24}$$

where t is the evaluations number of the current iteration; $evals_{\max}$ is the maximum assessments number; A_{init} and A_{final} are, respectively, the initial and final detection values of the explosion radius.

(2) New type of explosion spark generation

In the basic fireworks algorithm, the shifting distance generated in each dimension is equal when the fireworks produce the spark which greatly reducing the diversity of the spark population. In view of this defect, the enhanced fireworks algorithm used the mutation pattern to produce explosion spark with different dimensions on the various locations in the process of calculating the generated spark of fireworks [14]. The new type of explosion spark increases the population diversity of explosion spark.

The dimension selection methods of the enhanced fireworks algorithm and the basic fireworks algorithm are different. That of the enhanced fireworks algorithm is $z^k =$

$round(U(0,1))$, $k = 1, 2, \ldots, D$, where U (0,1) denotes a random number uniformly distributed in the interval of [0,1]. In the other word, the dimension choice number is distributed in [0-D] with a binomial distribution. However, the dimension selection method of the basic fireworks algorithm is $z = round\,(D \times U(0,1))$, and the shifting distances produced on each dimension are equal.

(3) New Gaussian mutation operator

In the basic fireworks algorithm, the position of the Gaussian variation spark x_{ik} will be close to zero when the randomly generated g value close to zero, and it is difficult to jump out latter; otherwise, it would result in x_{ik} beyond the boundary if g value is huge. The mapping rules of the fireworks algorithm may map x_{ik} near to the origin location.

To avoid this problem, a new Gaussian mutation operator [14] is proposed for the enhanced fireworks algorithm. The new Gaussian spark is calculated as follows:

$$x_{ik} = X_{ik} + (X_{BK} - X_{ik}) \times g, \tag{25}$$

where g is a Gaussian random variable with a mean value of 0 and a variance of 1; X_{Bk} is the position information of the fireworks in the kth dimension whose fitness value is the best in the current fireworks population.

(4) New mapping rules

In the basic fireworks algorithm, when a spark in a certain dimension k moves beyond the border, we can map it to a new location by the mapping rules of formula (20). However, since the optimal value of many optimization problems is at the origin position, the mapping rule will involuntarily and greatly accelerates the convergence speed of the algorithm, while it is not a result of the algorithm's intelligence, but an illusion. Based on this problem, the enhanced fireworks algorithm proposed a random mapping rule [14], which utilizes the following formula to map the spark exceeded the boundaries:

$$x_{ik} = x_{\min}^{k} + U(0,1) \cdot (x_{\max}^{k} - x_{\min}^{k}), \tag{26}$$

where U(0,1) is an uniformly distributed random number in the interval of [0,1].

(5) Elite-random selection strategy

In the basic fireworks algorithm, the selection strategy is based on the distance variable. However, since this choice method requires the Euclidean distance matrix between any two points in each generation of constructed populations, this will lead to a great time consumption of the basic fireworks algorithm. Therefore, an elite-random selection strategy [14] is proposed, in which the individual with the best fitness value is selected, and then the random selection strategy for the other fireworks is adopted. After the fireworks and Gaussian variation sparks are generated in the fireworks population, the enhanced fireworks algorithm chooses the individuals (elite) with the lowest fitness value from the fireworks, explosion sparks and Gaussian variation sparks as the fireworks of the next generation fireworks population firstly, and then selects randomly from the set of the rest fireworks.

3.3 Adaptive Fireworks Algorithm

Adaptive fireworks algorithm proposed an adaptive explosion radius mechanism [15] based on the enhanced fireworks algorithm. In the basic fireworks algorithm, the radius of the fireworks other than the optimal one is calculated per the difference between their fitness values and that of the optimal firework, but the explosion radius of the optimal firework is always zero. This means that the optimal firework does not contribute to the algorithm, but it generates the largest number of sparks. Optimal firework consumes the most resources but has no effect. The explosion radius of fireworks in basic fireworks algorithm and those of the rest fireworks in enhanced fireworks algorithm are calculated per equation (17), so it is adaptive, but the optimal fireworks radius is still a big problem.

Therefore, a minimum radius checking mechanism is employed to prevent the radius of the optimal fireworks from being zero. The core idea of the adaptive explosion radius mechanism is to use the spark that has been generated to calculate the explosion radius of the optimal fireworks. Calculate radius of the optimal firework in the next generation by using the information obtained from current generation.

To calculate the adaptive radius, an individual is selected, and the distance between the selected one and the optimal individual is used as the radius of the next generation explosion. The selected individual satisfies the following two conditions:

① The fitness value is worse than the fireworks of current generation.
② The distance to the optimal individual is the shortest among the individuals satisfying ①, which is:

$$\hat{s} = \arg\min_{s_i}(d(s_i, s^*)). \tag{27}$$

The following conditions are satisfied:

$$f(s_i) > f(X), \tag{28}$$

Table 1 Target data to be attacked

Target number	X-axis (km)	Y-axis (km)	Speed (m/s)	Direction angle (°)
T_1	1200	800	10	270
T_2	1280	800	10	270
T_3	1360	880	10	270
T_4	1360	720	10	270
T_5	1440	960	10	270
T_6	1440	640	10	270
T_7	1520	1040	10	270
T_8	1520	560	10	270
T_9	1600	1120	10	270
T_{10}	1600	480	10	270

Table 2 Data of each intelligent mine

Intelligent mine number	X-axis (km)	Y-axis (km)	Exit velocity direction angle (°)	Exit velocity elevation angle (°)	Exit velocity (m/s)
W_1	300	900	36	40	30
W_2	300	700	72	40	30
W_3	400	1000	108	35	30
W_4	400	800	144	35	30
W_5	400	600	180	35	30
W_6	500	1100	216	30	30
W_7	500	900	252	30	30
W_8	500	700	288	30	30
W_9	500	500	324	30	30
W_{10}	600	1000	360	25	30
W_{11}	600	600	36	25	30
W_{12}	600	800	72	25	30

where s_i represents all sparks generated by fireworks; s^* means that the fitness value is the best in all sparks and fireworks; X denotes fireworks; d is a measure of a certain distance.

Taking into account the explosion of fireworks in the enhanced fireworks algorithm which is explored independently in each dimension, the infinite norm ($\|x\|_\infty = \max_{i=1,2,\ldots,d}(|x_i|)$) is used as the distance measure. To further slow down the convergence rate to improve the global search ability, the adaptive radius being calculated above is multiplied by a specific coefficient λ, normally, $\lambda = 1.3$.

Considering the number of sparks in each explosion is limited, used a simple smooth mechanism $A(g+1) \leftarrow 0.5 \cdot (A(g) + A(g+1))$ to reduce the impact of particularly bad luck. Take the calculated adaptive radius and the explosion radius of this generation as the explosion radius of next generation.

4 Simulation Verification and Analysis

In the simulation experiment, there are 12 intelligent mines and each one carries three submunitions. Each intelligent mine is equipped with a full range of sensor systems with a detection radius of 300 m. The effective attack distances of the intelligent mines are 100 m. There are 10 target tanks to be attacked. The specific data are as follows: The data of attack targets are shown in Table 1, which include the plane position coordinates of each tank, traveling speed and driving direction angle; the data of each intelligent mine are shown in Table 2, which include the plane position coordinates of each intelligent mine, the direction angle for exit velocity of sub-ammunition, the elevation angle between the exit velocity of the sub-ammunition and the horizontal plane, and the sub-ammunition exit velocity $C = 2$; the indicator weights w_1, w_2, w_3 were taken as 0.3, 0.3, 0.4, respectively, $\lambda_1 = 0.7, \lambda_2 = 0.3$; there are 15 fireworks. The number of trials is 50. The maximum iterations number is 100. The evaluations number is 10000. Gaussian variation sparks are 20. Search space falls in [0,1.07].

Table 3 Task allocation result

Target number Intelligent mine number	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	Submunitions number of intelligent mines
W_1	0	0	0	0	0	0	0	0	0	1	1
W_2	0	0	0	0	0	0	0	0	0	0	0
W_3	0	0	0	0	0	0	0	0	0	0	0
W_4	0	0	0	0	0	0	1	0	1	0	2
W_5	0	0	0	0	0	0	0	1	0	0	1
W_6	0	0	1	1	0	1	0	0	0	0	3
W_7	0	0	0	0	0	0	0	0	0	0	0
W_8	0	0	0	0	0	0	0	0	0	1	1
W_9	0	0	0	0	0	0	0	0	0	0	0
W_{10}	0	0	0	0	0	0	0	0	0	0	0
W_{11}	0	1	0	1	1	0	0	0	0	0	3
W_{12}	1	1	0	0	0	0	1	0	0	0	3
Number of tanks were attacked	1	2	1	2	1	1	2	1	1	2	\

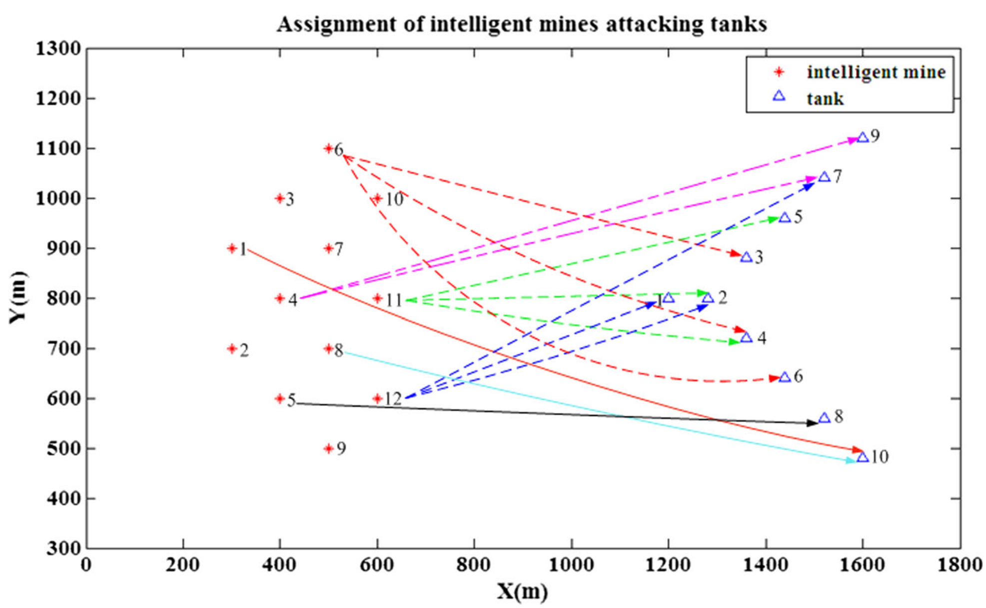

Fig. 2 Intelligent minefield attack targets assignment diagram

After simulation, the intelligent mine attack decision-making scheme is obtained. The results are shown in Table 3, in which all experimental results were averaged over 50 experiments. The data in the table represent the number corresponding to submunitions of each intelligent mine attacking targets. We can obtain the allocation diagram of intelligent minefield attack tasks which is shown in Fig. 2.

As can be seen from Table 3, each tank target was attacked by intelligent mines, and the same target was attacked up to twice which meets the constraints of $C = 2$. To attack all tank targets using a minimum number of intelligent mines, only 7 intelligent mines were used in the experiment, and the remaining 5 smart mines could be used as a subsequent force reserve. From Fig. 2, it is known that intelligent mines 2, 3, 7, 9 and 10 were not scheduled to attack the targets, and each target is attacked by at least a sub-ammunition.

To verify the effectiveness and superiority of the adaptive fireworks algorithm in dealing with this problem, the algorithms of FWA, AFWA, MIGSO, SA-DPSO and MIGA were used, respectively, in the experiment. Each algorithm carries out 50 simulation experiments, which are terminated until 100 times for each experiment. The five algorithms are compared experimentally, and the evolution curve is shown in Fig. 3.

From this figure, we can draw the following conclusions: MIGA and FWA algorithms not only converge slowly, but

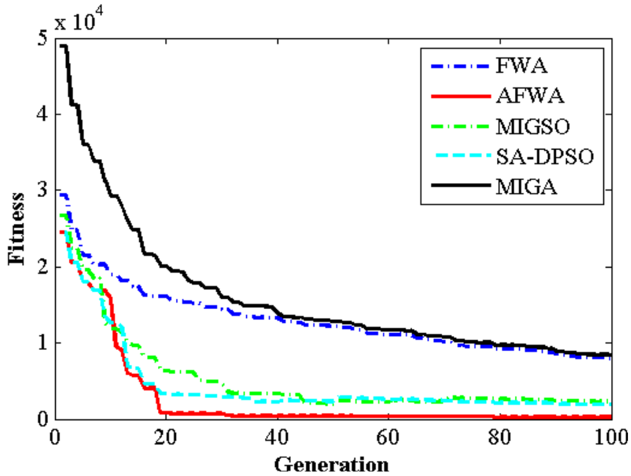

Fig. 3 Comparison of evolutionary curves corresponding to each optimization algorithm

also eventually fall into the local optimal solution; although the MIGSO algorithm basically converges to the global optimal solution, its convergence speed is the slowest among the five algorithms which needs almost to iterate at around 40 times to find the optimal solution, and the convergence oscillation occurs during the experiment; the convergence speed of SA-DPSO algorithm is fast and it basically converges to the global optimal solution. However, the performance of the AFWA algorithm which not only converges to the global optimal solution only after iterating 20 times, but also converges to the global optimal solution, is superior to the SA-DPSO algorithm. In solving this complex problem, the AFWA algorithm can find the optimal solution of the objective function at a very fast speed, and it only takes 5.8 s to complete all the iterations in the MATLAB environment.

5 Conclusion

In this paper, the problem of intelligent minefield attacking tank forces is studied. Aiming at the multi-constrained multi-objective nonlinear optimization problem, a new method is proposed to deal with the model by using the external penalty function method, which transformed multi-objective nonlinear optimization problem a non-constrained single-objective nonlinear programming problem. Aiming at the shortcomings of the current intelligent algorithms and combining with the characteristics of the fireworks algorithm, this paper proposes an adaptive fireworks algorithm to calculate the optimization problem.

In order to verify the superiority of adaptive fireworks algorithm to deal with this problem, experimental results show that the adaptive fireworks algorithm has faster convergence speed and shorter computation time than the other algorithms, and the results can visually represent the reasonable task allocation scheme in the complex situation, which provides the basis for the further control of force. This article provides a new feasible method to solve the multi-constrained multi-objective nonlinear optimization problem. At the same time, the optimization method used in this paper shows a good advantage over the traditional methods. And it has good generality for solving optimization problems, so that it is easy to put into engineering application.

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