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A New Method to Assess the Situation in Regional Air Defense Combat

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Abstract. In regional air defense combat, situation assessment is aimed at achieving rapid data fusion and providing quick assistance for the decision-making of commanders. In this paper, a new situation assessing framework of regional air defense combat is proposed. The new framework, in accordance with the combat process, is more concrete in a real combat context. The framework consists of three aspects: assessment of regional air defense capability, prediction of the enemy invasion route and generation of our interception plan. The regional air defense capability is evaluated and inferred by a Bayesian Network, whose evidence input is calculated by threat models: terrain, radar and antiaircraft firepower. After evaluation, the air defense weak area can be obtained. Then Particle Swarm Optimization is employed to predict possible enemy invading flight paths in air defense weak area. Moreover, to intercept enemy aircraft, the interception model is then built based on our attack modes to provide us with rapid interception pre-plans. The experimental results show the effectiveness of this new situation assessment method. Finally, the algorithm comparisons prove the advantage of PSO over other algorithms in this problem. Fast decision-making in regional air defense combat can be achieved with the support of the proposed method.

Keywords: assessment of regional air defense capability, Bayesian Network, generation of our interception plan, Particle Swarm Optimization, prediction of enemy invasion route, threat model

1 Introduction

Situation assessment belongs to a high-level information and data fusion process. In a military environment, situation assessment is an important part of command and control, and its main purpose is to support decision-making processes. Traditionally, situation assessment has been divided into three levels: observational situation, assessing situation and predictive situation [1]. However, these three levels in situation assessment cannot provide direct assistance to commanders because a strong connection has not been established between situation assessment and decision-making. In a real battle, what we focus on most is the situation that has the most impact on us and that can support us. If the assessment result submitted to commanders can be in a form of a situation of interest, then it can be more useful for their decision-making process. Consequently, we add a level into situation assessment after predictive situation: feedback situation. Feedback situation aims at providing commanders with auxiliary decisions directly, forming a bridge between battlefield situations and decision-making processes. It is designed to feed the three former situation assessing results back to commanders and then form a new situation to guide what should be done next. As a result, feedback situation is related more directly and can be the level that commanders mostly dependent on.

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To date, several achievements have been realized to assess battlefield situations. Zhu and Hu [2] used deep learning to design a nonlinear neural network, which adapts to the battlefield situation using big data; however, the assessing mechanism is hidden and cannot support the decision-making process. Lei et al. [3] developed intuitionistic fuzzy reasoning and applied it into situation assessment. This algorithm can represent the commanders' experience effectively; however, it is difficult to build the reasoning rules, which cannot realize intellectualized control. Li [4] constructed a Bayesian Belief Network to assess the battlefield situation; this approach mainly addresses the probability reasoning process and obtains a satisfactory result. As for situation prediction, many algorithms have also been developed. Nie et al. [5] constructed a Voronoi diagram of a battlefield and then searched for the best path. This type of graph-based method must be recomputed if the battlefield obstacles are changed, making it impractical in real applications. In [6], the terrain is first meshed and the cost function improved; subsequently, they used the A* searching algorithm to find the best flight path. Although this algorithm extends the flight paths from 2D space to 3D space, this improvement is not applicable to the most situations in 3D space. [7] used Particle Swarm Optimization to plan the path for an unmanned aerial vehicle. This method is easy to implement, and its planning time is short, thereby meeting the requirement of real-time path-planning. In the previous works [2, 4-7], the assessing situation and predictive situation are evaluated separately. In this paper, the assessing situation and predictive situation are combined and interact for the first time in a combat process. Then, the feedback situation is added; these three parts comprise the whole assessment framework.

This paper, using regional air defense combat as the background, focuses on the assessing situation, predictive situation and feedback situation, and the situation assessment method is reclassified according to the operational processes of regional air defense combat; this approach provides commanders with more intuitive and specific situation awareness. The three newly divided levels of situation assessment are as follows: assessment of regional air defense capability, prediction of enemy invasion route and generation of the interception plan. The assessment of regional air defense capability focuses on finding the air defense weak area; this approach belongs to the assessing situation. The prediction of the enemy invasion route, as the key module and the research emphasis, is to plan an optimal path in our air defense weak area for an enemy that avoids all the threat areas; this approach corresponds to the predictive situation. The generation of our interception plan is to build interception models based on our attack modes and the predicted route of the enemy that provides an interception flight path for our aircraft. This approach establishes a feedback situation that relieves commanders' workloads and supports their decision-making processes. Obviously, these three parts are closely linked with a sequence, and they can provide a clear combat process and early warnings to commanders in an actual battle.

In this paper, the air defense area is divided first. Moreover, threat models are built in the configuration space. For the problem of regional air defense capability assessment, a Bayesian Network (BN) is introduced to build an assessment network. With inputted evidence calculated by threat models, we can obtain the air defense weak area. Furthermore, the assessment result can drive the prediction of an enemy invasion route and the generation of our interception plan. On one hand, Particle Swarm Optimization (PSO) is used to search for the optimal path of enemy aircraft in our air defense weak area; because PSO has few parameter settings, high searching efficiency and lower complexity, it can perform this task very well. On the other hand, our interception pre-plan is generated by modeling enemy flight paths and our attack modes, that is, counter attack and stern attack, which provides our aircraft with interception flight paths. The whole modeling structure is shown in Fig. 1.

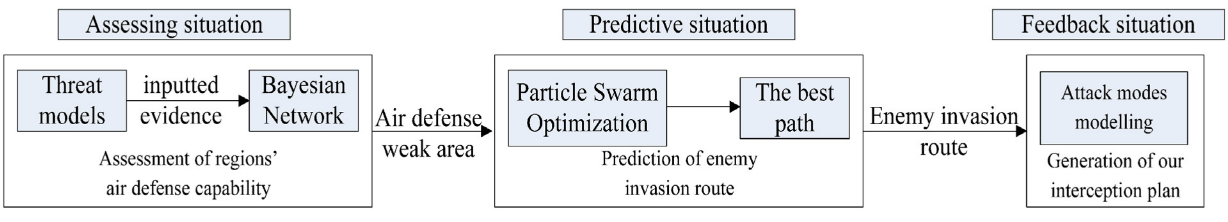

Fig. 1. Structure of the work in this paper

The simulation and algorithm comparison are implemented in the last section. The simulation results show that the proposed situation assessment methods can rapidly assess the regional combat capability and provide the air defense weak area. As the key part in this work, the enemy invasion route is predicted by the PSO. To prove the performance of PSO, we compare PSO with the Voronoi graph model in [5]. The computational results show that PSO can generate a smoother and shorter flight path, which contributes to aircraft safety. Finally, the generation of our interception plan is simulated. The experimental results show that commanders can obtain auxiliary decisions effectively and quickly. The whole algorithm improves the efficiency of the decision-making process.

2 Assessment of the Regional Air Defense Capability in the Assessing Situation

2.1 Establishment of the Air Defense Area

For the assessment of the regions, the establishment of an air defense region is a basic task. In Fig. 2, it is assumed that our defended site is the coordinate origin. Let the east direction be the X-axis, the north direction be the Y-axis and the vertical direction be the Z-axis. Thus, our defense line is a circle centered on our defended site, whose radius is R_f. In addition, the interception line is another concentric circle whose radius is designated one third that of the defense line, denoted as $\frac{1}{3}R_f$. Based on the above coordinate system, the whole configuration space can be divided into several sub-fan-shaped columns denoted as $L_1, L_2, \cdots, L_n$. One column represents an air defense area (see Fig. 3).

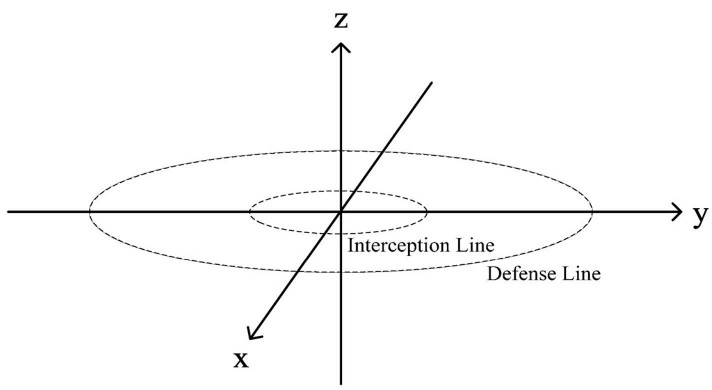

Fig. 2. Model of the configuration space

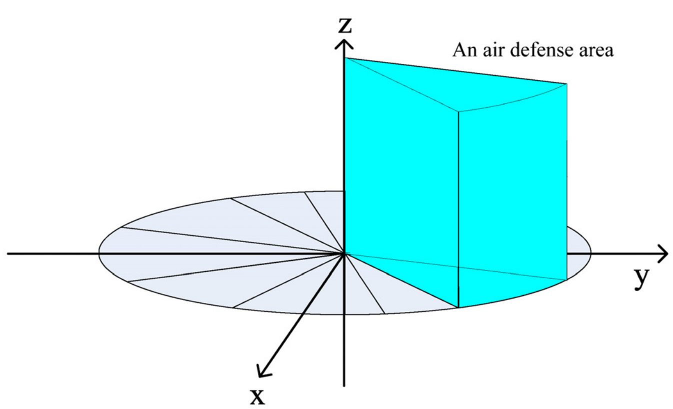

Fig. 3. Typical establishment model of the air defense area

2.2 Threat Area Models

The primary step to assess the regional air defense capability is to describe the threat areas in configuration space. Generally, if there are more dangerous threat sources in one region, then its air defense capability must be high. The model of the threat areas lays a foundation for the next steps and has an effect on the prediction of the enemy route.

Terrain threat. Terrains are the main obstacles of aircraft, and mountains are the most common terrain threat. The terrain can be generated by a combination of different mountains, high or low. Thus, we select the formula of a mountain to describe the terrain threat [8]:

$$z(x,y)=\sum_i h_i \cdot exp[-(\frac{x-x_i}{k_i})^2-(\frac{y-y_i}{k_i})^2], \quad \textbf{(1)}$$

where h_i , (x_i, y_i) , and k_i are the altitude, center coordinate, and gradient of the i th mountain, respectively. Fig. 4 shows a simulation of a typical terrain.

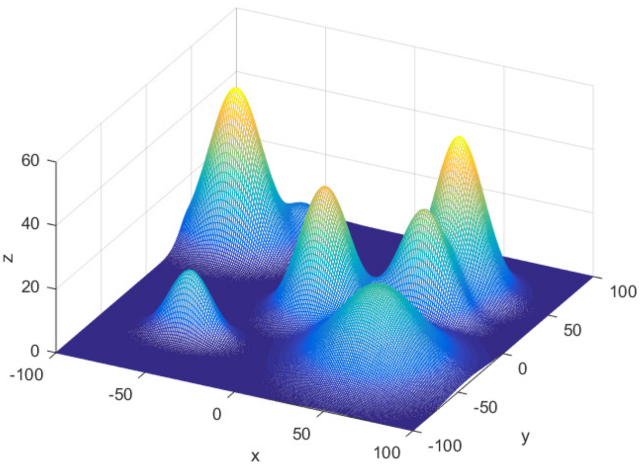

Fig. 4. Simulation of a typical terrain

Radar threat. If the aircraft can avoid radar detection, then they will complete the tasks in a safer manner. Therefore, radar threat is another means to enhance the ability of air defenses. In the radar threat model, its detection range and efficiency should be first considered. After reading some references [9], the relationship between the detection height of the radar threat and the distance to the center of the radar can be given as:

$$z_i(x,y)=K_h \cdot ({R_{max}}^2-(x-x_i)^2-(y-y_i)^2), \quad \textbf{(2)}$$

where $z_i(x,y)$ is the detection height of i th radar, $(x_i, y_i, 0)$ is its center coordinate, K_h is the factor of radar detection performance and $R_{\max}$ is the maximum detection range of the radar. Fig. 5 shows a simulation diagram of the detection range of several radars.

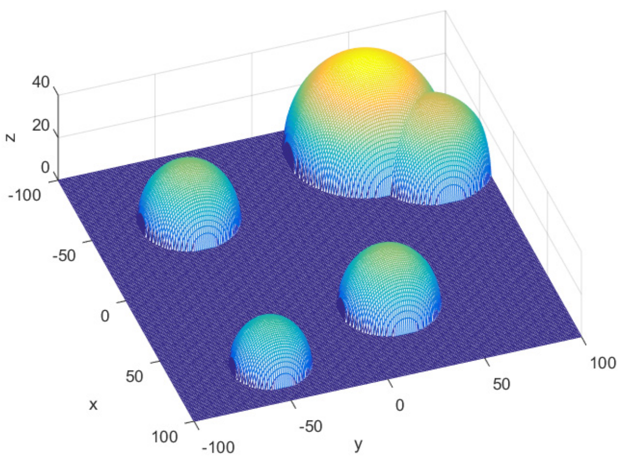

Fig. 5. Simulation of the detection range of radars

Anti-aircraft firepower threat. When an aircraft is detected by radar, it must keep away from the anti-aircraft firepower threat to ensure safety. Moreover, anti-aircraft firepower is the most dangerous and direct threat among the relevant threats. Thus, it is a key threat source to improve the air defense capability. In this paper, we mainly consider the model of air defense missiles and artillery [9]:

$$z_i(x,y)=\frac{(R_0{}^2-(x-x_f)^2-(y-y_f)^2)}{R_0}, \quad \textbf{(3)}$$

where $z_i(x,y)$ is the equivalent elevation of the i th anti-aircraft firepower threat, (x_f, y_f, z_f) is its coordinate and R_0 is the maximum operating range. Fig. 6 shows the simulation of a typical anti-aircraft firepower threat.

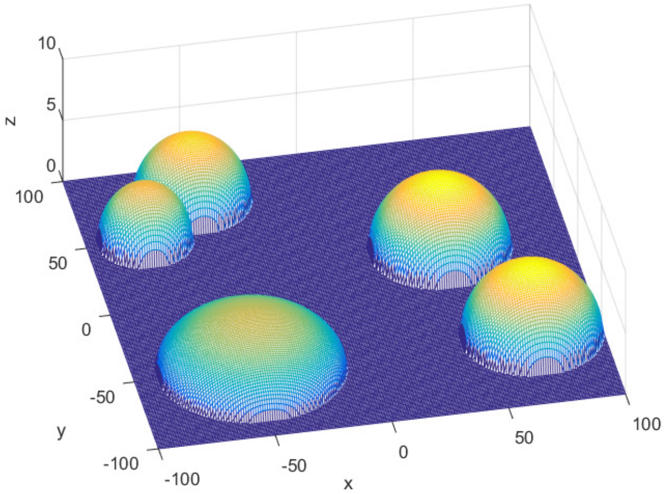

Fig. 6. Simulation of a typical anti-aircraft firepower threat

2.3 Bayesian Network for the Regional Air Defense Capability Assessment

Usually, the commanders assess a regional air defense capability artificially. However, in a real battle, various and swiftly changing situations drive us to provide a method to assess the regional air defense capability rapidly and rationally. Moreover, there is an increasing demand for a tool to perform capability assessment. The regional air defense capability is a comprehensive index that involves many complex factors and diverse influencing parameters. Its assessment process must combine subjective judgment with objective data. In this case, simple empirical models cannot meet the requirement, and the ideal model must involve both empirical information and mechanical data.

A Bayesian Network (BN) has great potential for use in assessment modeling because it can represent uncertainty knowledge in a concise manner. Moreover, the reasoning process of a BN conforms to human cognition, thus ensuring the result is acceptable to commanders. As a result, a BN is an ideal tool to address the problem of situation assessment.

BN structure modeling. This section offers a BN structure to illustrate the assessment of a regional air defense capability (see Fig. 7). The top-level node represents the air defense capability of a region and has three states: strong, medium and weak. The hidden-level nodes show the three factors related to air defense capability, and the observation nodes consist of influencing parameters of each type of threat. By inputting the evidence from sensors, the BN can draw conclusions from the top-level node and provide us with the air defense weak area [10].

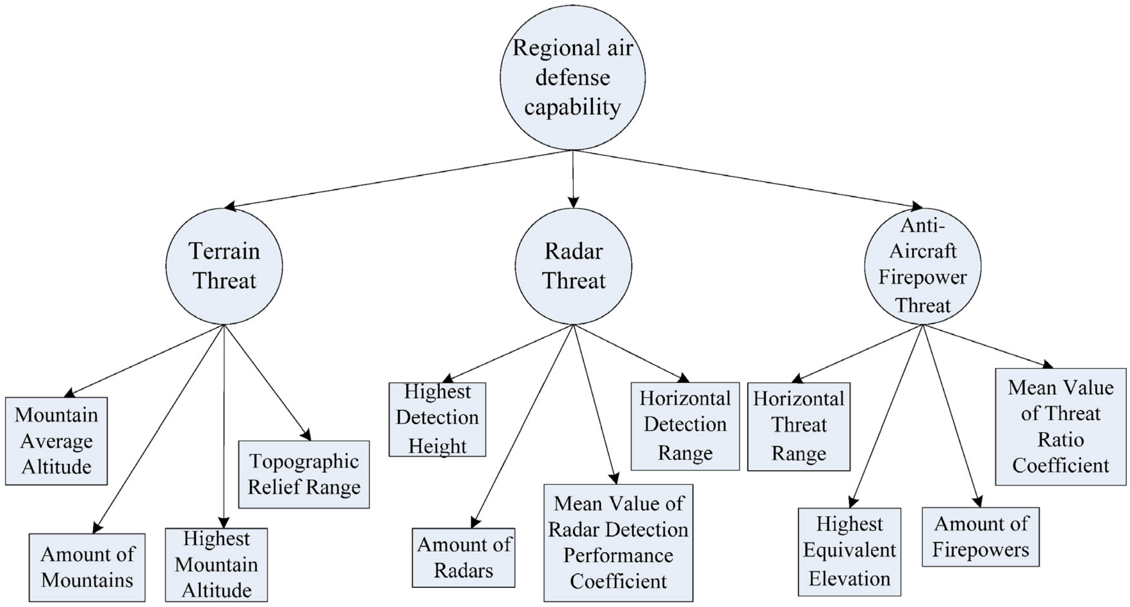

Fig. 7. BN structure model

Evidence extraction and discretization. When new information can be extracted as evidence, probabilities in a BN will be updated and inferred [11]. If some nodes are observed to be a determined value, then this evidence will be disseminated through the whole network, and the rest of the nodes will change their joint posterior probabilities [12]. The evidence of a BN in the assessment of regional air defense capability is calculated using threat area models. We take the terrain threat as an example to show how to extract the evidence. The topographic relief range qualifies the terrain barrier of the air defense. Let T_i be the topographic relief range of the i th mountain; it can be calculated by:

$$T_i = \pi k_i^2 ln \frac{h_i}{G}, \tag{4}$$

where G is the altitude of the lower boundary in the air defense region. Hence, the whole topographic relief range T of mountains in a single air defense region is the union of each mountain's topographic relief:

$$T = T_1 \cup T_2 \cup \cdots \cup T_n . \tag{5}$$

For the purposes of computational limitation, a BN prefers discretization variables. Thus, after obtaining the data, it must be discretized. One method to discretize the data is to build the membership function. If the whole topographic relief range is wider than a threshold S, then it can be considered as a wide range. The membership function of the topographic relief range can be built as:

$$E_T = \begin{cases} wide\ range, & F_{terrain} \geq S \\ small\ range, & F_{terrain} < S \end{cases}. \tag{6}$$

E_T is the observation evidence of the node *topographic relief range*.

Conditional probability table. The Conditional Probability Table (CPT) gives us the probability distribution of nodes based on their parents. CPT is a representation of the combination of expert knowledge and objective information. Usually, CPT can be generated by parameter learning; that is, an amount of data is used to train the network and obtain the probability of each node. However, because of the limited amount of data, we provide an example of CPT of a BN fragment with the aid of domain expert knowledge.

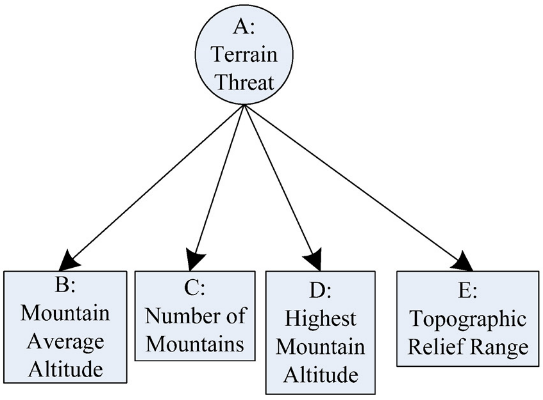

Fig. 8. BN fragment

Fig. 8 shows a BN fragment with 5 nodes. A is a hidden-level node with three states: strong, medium and weak. The CPT for observation nodes B, C, D, and E is given in Table 1.

Table 1. CPT for nodes B, C, D, E in Fig. 7

Probability	B		C		D		E	
Terrain Threat	High	Low	Many	Few	High	Low	Wide	Small
Strong	0.7	0.3	0.75	0.25	0.8	0.2	0.85	0.15
Medium	0.4	0.6	0.5	0.5	0.5	0.5	0.55	0.45
Weak	0.1	0.9	0.2	0.8	0.1	0.9	0.15	0.85

Bayesian inference. Once the BN and the CPTs have been built and acquired, they can be used to perform network inference. Network inference can be considered as calculating the posterior probabilities of the unobserved nodes [12-14]. Suppose that an unobserved node is X, its parent nodes collection is $U=\{U_1,U_2,\cdots,U_n\}$, the child nodes collection is $Y=\{Y_1,Y_2,\cdots,Y_n\}$, e is the collection of evidence nodes, e_X^+ is the evidence nodes collection that connects with X through its parent nodes, and e_X^- is the evidence nodes collection that connects with X through its child nodes. Thus, the information that is updated by parent nodes collection marked with $\pi(x)$ is given by:

$$\pi(x)=\sum_{u_1,\cdots u_n} p(x\,|\,u_1,\cdots u_n)\prod_{i=1}^{n}\pi_x(u_i)\,. \tag{7}$$

The information propagated by child nodes collection is given by $\lambda(x)$:

$$\lambda(x)=\prod_{j=1}^{m}\lambda_{Y_j}(x)\,. \tag{8}$$

Synthesizing the whole information that is transferred to X through its parent nodes collection and child nodes collection, the posterior probability of X under the condition of the observed evidence is:

$$p(x\,|\,e)=\alpha\pi(x)\lambda(x)=\alpha[\sum_{u_1,\cdots u_n} p(x\,|\,u_1,\cdots u_n)\prod_{i=1}^{n}\pi_x(u_i)][\prod_{j=1}^{m}\lambda_{Y_j}(x)]\,, \tag{9}$$

where $\alpha=p(e_X^+)\big/p(e_X^+,e_X^-)$ is a normalization constant. Next, we can infer each region's air defense capability and output the result. If a region's air defense capability is *weak*, then it will be judged as an *air defense weak area*.

3 Prediction of the Enemy Invasion Route in the Predictive Situation

When enemies want to attack our defended site, they must choose our air defense weak area as their breakthrough point. Based on the above result of the air defense weak area, we can suppose that the enemy may plan a flight path in this area to invade. Therefore, considering the air defense weak area as the configuration space, we must predict a flight path that can avoid all threat areas as the enemy's invading route and make this the main part of the predictive situation.

In the second section, we built the threat models. We now see these threat sources in path-planning as the terrain that has the same shape contour as the threat and make the aircraft avoid them. In this manner, the optimal path can be easily searched in the configuration space.

Because aircraft in air strike missions always fly at a low or ultra-low altitude, we assume that enemy aircraft set out from the intersection of the air defense weak region midline and defense line, and their destination is our defended site. The start and goal are marked with (x_{iq}, y_{iq}, z_d) and $(0,0,0)$, respectively. We select several nodes between start and goal, whose x coordinates are randomly designated or evenly spaced. Thus, the collection of selected nodes combined with start and goal is connected to form a complete flight route. This route can be represented by [15]:

$$P_i = [(x_{iq}, y_{iq}, z_d), (x_{i1}, y_{i1}, z_{i1}), \cdots, (x_{i,m}, y_{i,m}, z_{i,m}), (0,0,0)], \tag{10}$$

where P_i is the i th route in the air defense weak area, and $(x_{i,m}, y_{i,m}, z_{i,m})$ is the m th node in the generated route.

The performance indicator of the enemy flight route consists of three parts: the threat cost, the distance cost and the height cost; thus, we design the performance indicator of flight route as:

$$\min J = \gamma_1 f_t + \gamma_2 f_d + (1\text{-}\gamma_1\text{-}\gamma_2) f_h, \tag{11}$$

where f_t, f_d, and f_h are the threat cost, distance cost, and height cost, respectively.

To solve the performance indicator, swarm intelligence (SI) can be introduced in this paper because it has been proved to be effective for solving optimization problems. SI-based algorithms are popular in modern engineering fields, of which, particle swarm optimization (PSO) is one of the most widely used. PSO, inspired by predation behavior of birds when hunting for prey, has a strong versatility [16-18]. PSO only needs the performance indicator to conduct the algorithm. Moreover, PSO is easy to operate and can be used to conduct a comprehensive search. Although PSO has some disadvantages, such as the lack of local search capability, PSO can meet the requirements of our problem, and it can be used in this paper to find the solution quickly.

In PSO, each particle is defined by its position x_m^k, velocity v_m^k, its best position up to the k th iteration p_m^k and the best position among the swarm up to the k th iteration p_g^k. The new position and velocity after iterating k times is given by:

$$v_m^{k+1} = \omega v_m^k + c_1 * \xi(p_m^k - x_m^k) + c_2 * \eta(p_g^k - x_m^k), \tag{12}$$

$$x_m^{k+1} = x_m^k + \gamma v_m^k, \tag{13}$$

where ω is the inertia weight to regulate global search behavior, c_1 and c_2 are adjustable factors that are typically set to a value of 2, and ξ, η and γ are random numbers ranging from 0 to 1. A particle is deemed sufficient according to its fitness value, that is, the performance indicator. After satisfying a certain limited number of iterations, the algorithm will terminate and output the best position and fitness value. In the problem of enemy route prediction, each particle represents a single route, which consists of several nodes, and the initial population is designated randomly. Moreover, the fitness function is the performance indicator that tells us whether the route can avoid the threat areas and satisfy the distance cost. When the iteration is completed, the best position of the particle is interpreted as a flight route, and we consider it as the invasion route of the enemy.

4 Generation of the Interception Plan in the Feedback Situation

To feed back the result of the situation assessment to the commanders, we must prepare for the assessment result of the predictive situation; that is, we must change our situation and make plans for the attack. Only in this manner can the commanders have options when meeting the enemy's attack. As the key in the feedback situation, the generation of our interception plan aims at planning the flight route for our interceptors to encounter the enemy. This is the best response to the predictive situation. Moreover, by submitting the situation result to commanders in a form of what we should do, we can support commanders to a great extent. In this section, we will model the interception plan in a practical and simple manner based on different attack modes.

4.1 Interception Plan Based on the Counter Attack Mode

The counter attack mode attacks the enemy from its front or diagonally ahead. This mode can apply to the situation that the capability of the enemy is weaker than us or at least equally competent to us. Suppose that the airport of our aircraft is (x_0, y_0, z), whose speed is V_w. After maneuvering, the enemy aircraft will fly towards our defended site, and it is assumed that enemy's current position is (x_{iq}, y_{iq}, z) in the air defense weak area L_i, and the enemy's speed is V_w according to the measurement. The height of our aircraft can be adjusted during flight, so long as it can keep pace with the enemy's height (marked by z) at the stage of attack [19].

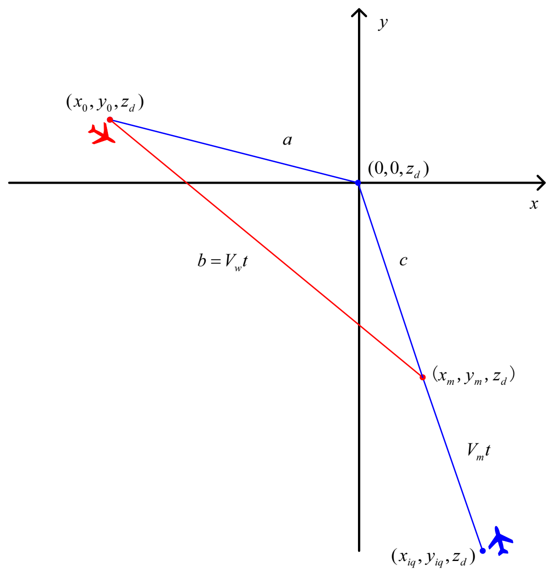

Fig. 9. Situation of the counter attack

Fig. 9 shows the attack mode of the counter attack and the situation between the enemy and our interceptor. The red line is the flight path of the interceptor, and the blue line is the enemy's flight path. Suppose that two aircraft encounter each other at scheduled attack point (x_m, y_m, z) on the interception line and the flight time before the encounter is t. Therefore, the counter attack can be modeled as:

$$\begin{cases} x_m = \dfrac{\frac{1}{3}R_f}{\sqrt{x_{iq}^2 + y_{iq}^2}} x_{iq} \\ y_m = \dfrac{\frac{1}{3}R_f}{\sqrt{x_{iq}^2 + y_{iq}^2}} y_{iq} \\ t = \dfrac{\sqrt{x_{iq}^2 + y_{iq}^2} - \frac{1}{3}R_f}{V_m} \\ V_w = \dfrac{\sqrt{(x_m - x_0)^2 + (y_m - y_0)^2}}{t} \end{cases} . \quad \textbf{(14)}$$

Based on the above model, the initial flight path of our interceptor is $(y - y_0) = \dfrac{y_m - y_0}{x_m - x_0}(x - x_0)$.

4.2 Interception Plan Based on the Stern Attack Mode

The stern attack mode is a method to attack enemy aircraft from its back and side; this mode contributes to our concealment. Thus, path-planning for the interceptor involves the interceptor reaching the scheduled attack point behind the enemy within the appropriate period and attacking the enemy in a favorable position. We model this attack mode as follows. Specify the initial situation of the interceptor arbitrarily according to two parameters: position p_0 and heading φ_0 . If the interceptor reaches the scheduled attack point in a favorable position, then it must be in a certain terminal situation: position p_t and heading φ_t . To guide the interceptor from the initial situation to the terminal situation, we use the two-turn method [19]. Through this method, the interceptor can realize conversion from any initial situation to any terminal state. Fig. 10 shows the two-turn model.

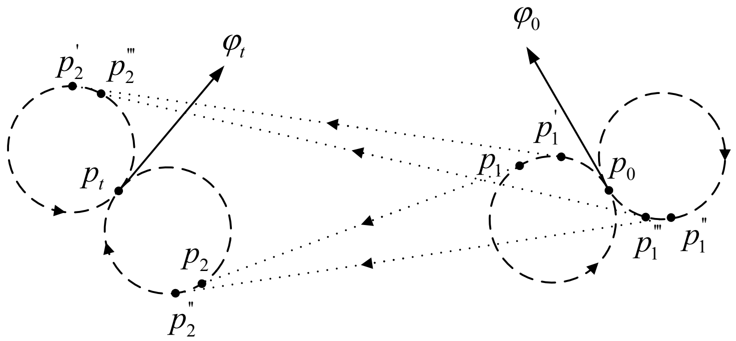

Fig. 10. Two-Turn Model

Supposing the turning radius of the interceptor is designated the minimum allowable turning radius, it can be seen that there are no more than four routes that allow the interceptor to complete the transition: $p_0p_1p_2p_t$, $p_0p_1'p_2'p_t$, $p_0p_1''p_2''p_t$, and $p_0p_1'''p_2'''p_t$. We must calculate the distances and choose the shortest one.

Applying the two-turn method to the stern attack mode helps build the model. Fig. 11 shows the stern attack modes based on the two-turn method. Supposing that the scheduled terminal situation is given by position p_t and heading φ_t , and the scheduled relative azimuth is 60° , the four possible flight paths for interceptor can be planned. After calculating the distances and choosing the shortest one, we can obtain the optimal interception pre-plan.

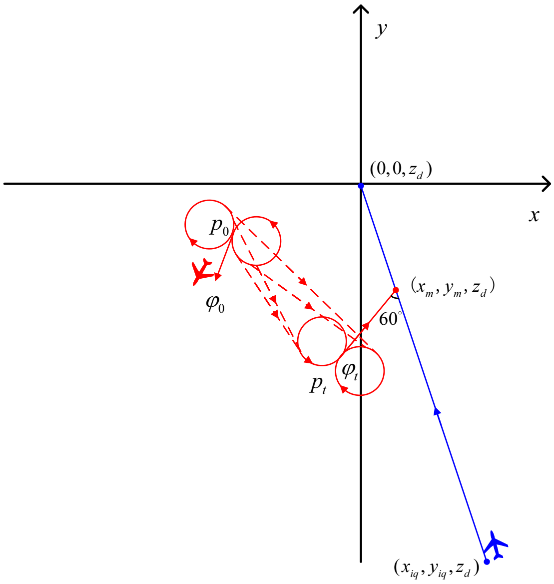

Fig. 11. Stern attack modes based on the two-turn method

Our interception plan can provide commanders with options and assistance when the enemy attacks us suddenly. The interception plan is the main part of the feedback situation. The feedback situation is a bridge between the situation assessing result and the commanders' decision-making process. In this period, the situation can be fed back to the commanders; this approach is a significant mean to generate our combat strength.

5 Simulation Experiments

In this section, the performance of the proposed situation assessment method is proved by several experiments and comparisons. Because the situation assessment is divided into three levels, three simulation scenarios are demonstrated in the following.

5.1 Simulation One

Assessment of the regional air defense capability is conducted in simulation one. The radius of our defense line is designated 100. To better simulate the real terrain, the number, position and range of threat areas are generated randomly. Fig. 12 shows the randomly generated abstract scene of threat areas in a 3D perspective. Fig. 13 shows the 2D diagram of threat areas (red). We divide the whole air defense area into 8 regions evenly and mark them from 1 to 8 in a counter-clockwise direction. Region 1 is located next to the positive X-axis. Fig. 14 shows the division of the air defense area.

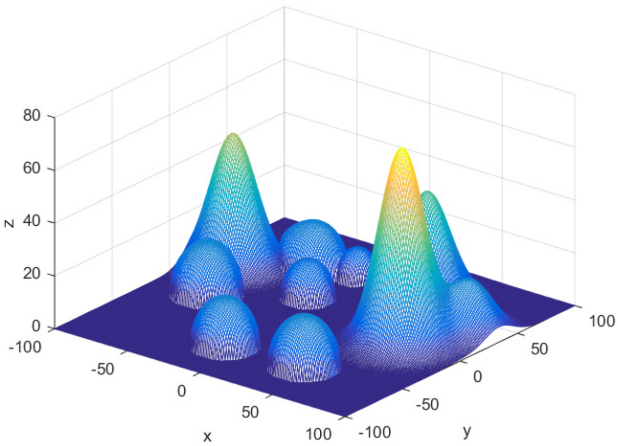

Fig. 12. Abstract scene of the threat areas in a 3D perspective

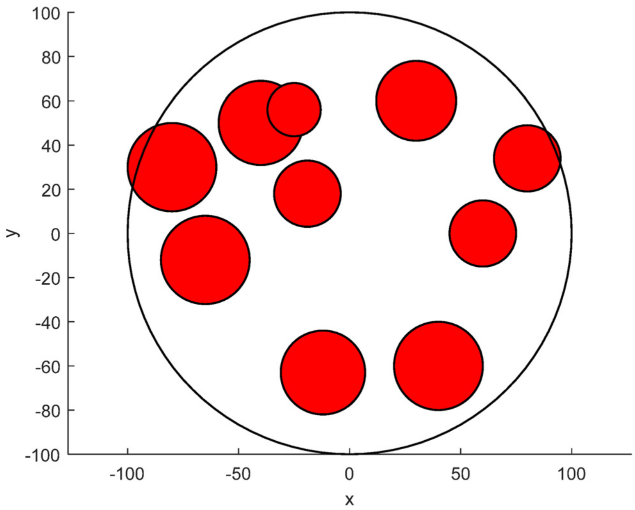

Fig. 13. 2D diagram of the threat areas

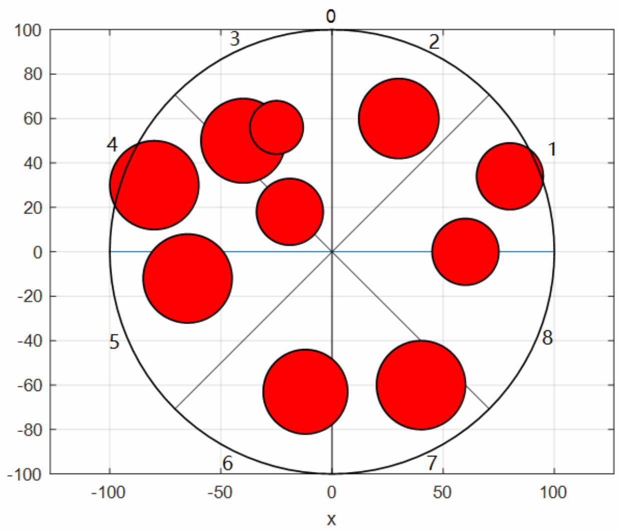

Fig. 14. Division of the air defense area

To conduct the assessment of the regional air defense capability, GeNIe2.0 is introduced to build the BN and perform inference. GeNIe2.0 is a practical software that allows users to build a BN and conduct a situation assessment. We build the network structure shown in Fig. 15. After we designate all the conditional probabilities of nodes, we can input the evidence observed from the battlefield. The assessment result of Region 4 as an example is illustrated in Fig. 15. From Fig. 15, we find that the terrain threat of Region 4 is medium because the heights of mountains are low, although there are many mountains in this region. The radar threat and anti-aircraft firepower threat are both high because they all have advantages in quantity and quality. Because of the important deployment of radar threat and anti-aircraft firepower threat, the whole air defense capability of Region 4 is high.

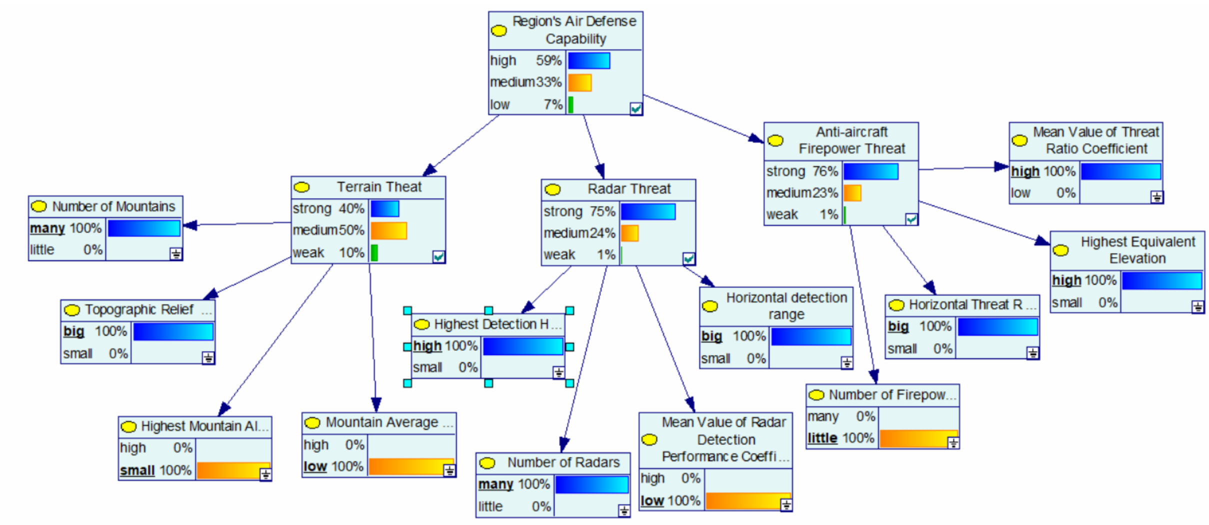

Fig. 15. The structure of BN in the assessment of regional air defense capability

The entire assessment result is shown in Table 2. We know the air defense weak area is Region 1 shown in Fig. 16 (dark red area). The reason why Region 1 is the air defense weak area is the limited range of the threat area. Even worse, there is no radar and anti-aircraft firepower threat in Region 1: only mountains. Regions 3 and 4 have a wide range of threat area, which contributes to their strong air defense capability. Although Regions 2, 5, 6, 7, and 8 have only one threat area, it is either with high altitude or with a strong threat coefficient that poses a medium threat to the enemy. Thus, from Fig. 12 and the deployment of all regions, we can conclude that the assessing results are in accordance with the actual situation.

Table 2. Assessment result

Air Defense Region	Air Defense Capability	Air Defense Weak Region
Region 1	weak	yes
Region 2	medium	no
Region 3	strong	no
Region 4	strong	no
Region 5	medium	no
Region 6	medium	no
Region 7	strong	no
Region 8	medium	no

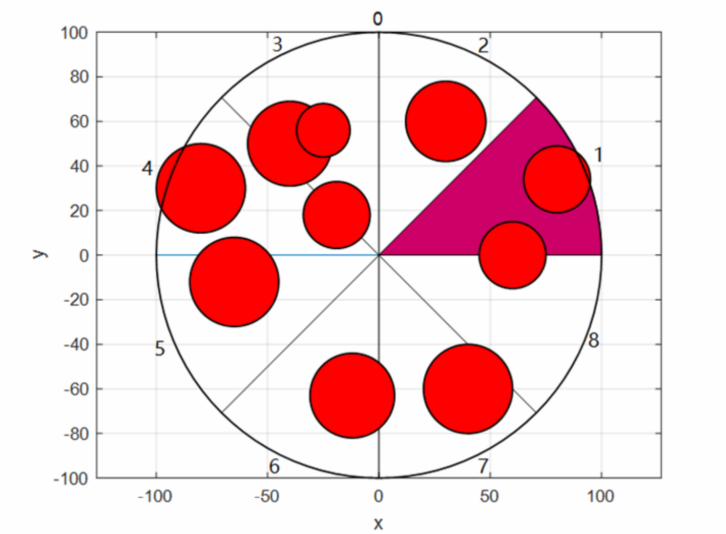

Fig. 16. Diagram of the air defense weak area

5.2 Simulation Two

Prediction of the Enemy Invasion Route is simulated in this section. We use PSO to generate the enemy flight path. To prove the performance of PSO, we compare it with a classic path-planning algorithm, i.e., the Voronoi graph model.

Because of the air defense weak area, we can reduce the route planning space into Region 1. The parameters of PSO and the constraint conditions are as follows. The number of random generated nodes is 100 with a dimension of 18, that is, there are 9 nodes in the flight route, except the start and the goal. We randomly disseminate the particle in configuration space and perform several iterations. Next, we can obtain the optimal path. Fig. 16 shows the final 3D route of the enemy (blue line). Table 3 gives the global best flight nodes generated by PSO. As shown in Fig. 17, the flight path can avoid all the threat areas effectively. In the air defense weak area, Region 1, there are two mountains that pose a threat; the best strategy is not to detour but to leap over the mountains. In this manner, the aircraft can reach the end with the shortest route. Moreover, we can see that the path of the aircraft is close to the terrain; this path can avoid detection by radars. The reason why PSO performs very well is because we designed a perfect performance indicator (Equation 11). This performance indicator can measure whether the generated path is adequate to be selected as a predicted plan of the enemy invading route.

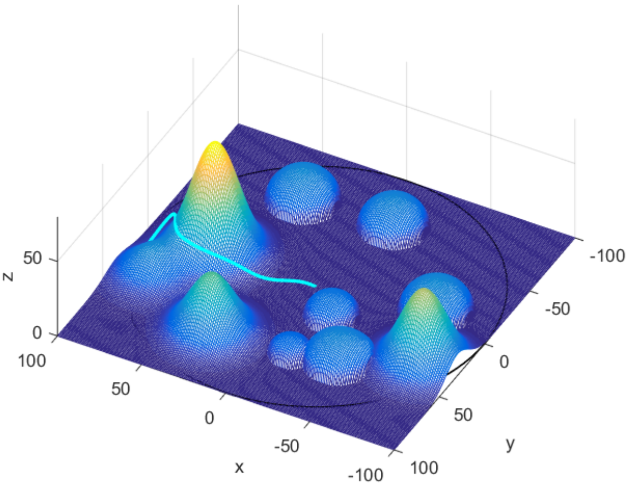

Fig. 17. Final 3D route of the enemy

Table 3. Global best flight nodes

Coordinate	Start	Node 1	Node 2	Node3	Node 4	Node 5
x	92.38	83.14	73.91	64.67	55.43	46.19
y	38.26	4.48	17.79	23.89	23.09	20.33
z	0	19.98	24.8	23.82	20.58	16.94
Coordinate	Node 6	Node 7	Node 8	Node 9	Goal	
x	36.95	27.71	18.47	9.23	0	
y	16.32	13.59	10.61	6.36	0	
z	11.43	6.72	5.16	4.96	0	

5.3 Simulation Three

Generation of our interception plan is simulated in this section based on the predicted flight route of enemy. We randomly designate the current position of our interceptor, which is marked by in the picture. Interception pre-plans with counter attack mode and stern attack mode are shown in Fig. 18 and Fig. 19, respectively. The red line represents the flight route of our interceptor, and the blue line represents the enemy's predicted flight route. This simulation is performed to prove that the proposed model can generate the interception plan quickly. The simulation result is used to provide an intuitive judgment and support the commanders' decision-making process. This approach is required because, if the enemy attacks us suddenly, there will be a short time for us to react. Moreover, this proposed model can provide us with the initial course of our aircraft. Although simple, the proposed model can play a great role in real combat, especially in a situation with limited time.

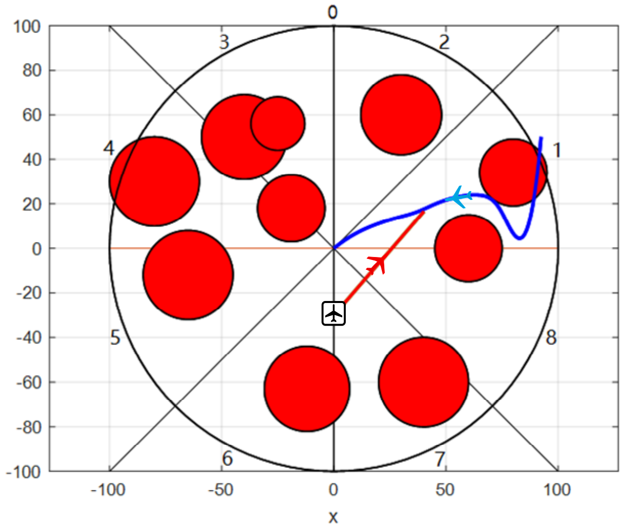

Fig. 18. Interception plan based on the counter attack mode

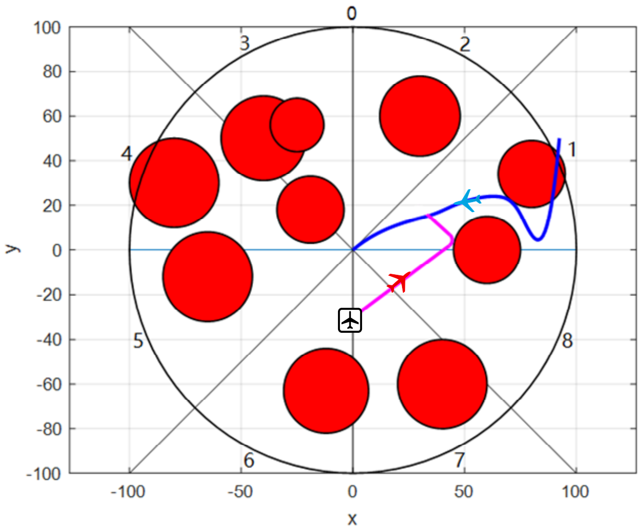

Fig. 19. Interception plan based on the stern attack mode

5.4 Algorithm Comparisons

In [5], Nie et al. used the Voronoi graph model, which is a classic model to plan the path for aircraft. The Voronoi graph model converts the path-planning problem into a region-division problem. By calculating the cost of the edge of region, we can find the best route. We use the Voronoi graph model to divide Region 1 in Fig. 16; Fig. 20 shows the result. The cost of each edge is determined by their distances to the threat areas. In addition, after we calculate the cost, we find that the best route in Region 1 is the blue route in Fig. 21.

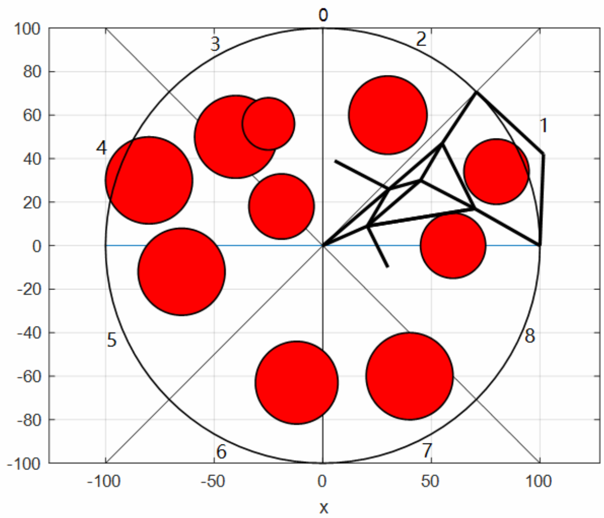

Fig. 20. Division result of region 1 by the Voronoi graph model

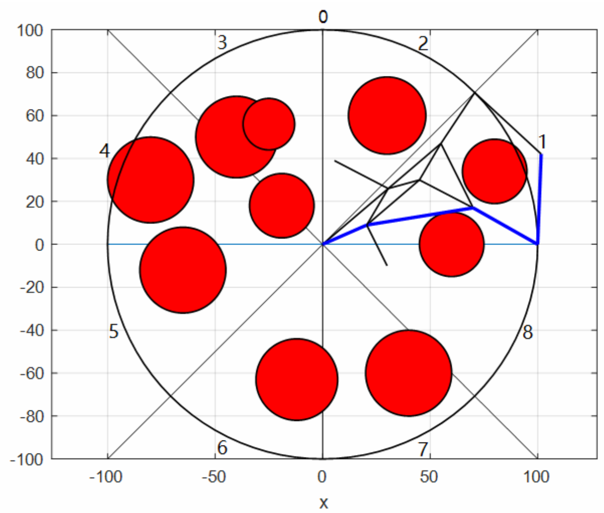

Fig. 21. The best route generated by the Voronoi graph model

From the result in Fig. 18, we can conclude that the path generated by the Voronoi graph model is approximately the same as the path generated by PSO. This agreement proves the generated path in PSO is correct. However, from the comparison, we find that the path in PSO is better than the path in the Voronoi graph model because of the following aspects. First, the path in PSO is smoother, i.e., the aircraft performs fewer maneuvers, thereby enhancing the safety of the aircraft. Furthermore, the path generated by PSO is in three dimensions. Thus, the path takes the height changes of aircraft into account; this approach is more practical in real air combat. Moreover, the path generated by PSO is slightly shorter than the path planned by the Voronoi graph model. The path obtained by PSO is 142.95, and the path generated by Voronoi graph model is 149.13. Therefore, we find that PSO has advantages to generate the flight path, as shown in Table 4.

Table 4. Comparisons between PSO and the Voronoi graph model

Comparisons	PSO	Voronoi graph model
Form of path	smooth	Have turning points
Dimension	3D	2D
Distance	142.95	149.13
Sudden maneuvering times	0	3

6 Conclusion

This paper presented a new proposed method to assess the situation in regional air defense combat for the purpose of decision-making. In accordance with the combat process, situation assessment was divided into three parts in a new manner: assessment of regional air defense capability, prediction of enemy invasion route and generation of our interception plan. To conduct the assessment of regional air defense capability, threat areas were first represented by function models. A Bayesian Network (BN) was introduced to build the assessment structure of the regional air defense capability. After inputting the evidence calculated by threat area models, BN completed the assessment rapidly and generated the air defense weak area. The enemy invasion route in the air defense weak area was predicted using particle swarm optimization (PSO) as a successful global planner. To provide the above situation information to commanders and relieve their pressure, an intercepting pre-plan is modeled based on different attack modes: counter attack mode and stern attack mode. Simulation experiments showed that the newly proposed method can assess the situation in air defense combat successfully. The proposed method also provides rapid and accurate decision-making for commanders. The algorithm comparisons also prove that PSO has advantages over the Voronoi graph model in this problem.

Future research can be conducted by clarifying the following problems. Some strategy can be introduced to improve the algorithms, such as local optima entrapment in PSO. In addition, other types of threat areas should be considered, even though most threatening types are already modeled.

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