Target Threat Assessment of Airborne Based on IT2F-BWM

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Abstract. Aiming at the problem of irrational application of indicator constant value weights in dynamic airborne threat assessment, an IT2F-BWM-based airborne target threat assessment method is proposed. Firstly, according to the characteristics of air combat confrontation, the threat assessment index model is constructed from the static and dynamic attributes of warplanes, and expert experience is integrated into the identification of combat intent; secondly, a fuzzy weight dynamic adaptation mechanism based on situational classification is designed, and IT2F-BWM is used to establish the mapping between typical styles and threat indexes, and the constrained optimization model is used to solve for the consistency of the optimal weights, and the dynamic adjustment of weights is realized with the evolution of the situation; finally, the effectiveness of the method is verified through comparative experiments. Finally, the effectiveness of the method is verified through comparative experiments, and the results show that the dynamic weights are more suitable for the real air confrontation requirements.

Keywords: Interval Type-2 Fuzzy, Best-Worst Method, Dynamic weighting, Threat assessment.

1 Introduction

Modern airborne confrontation is accelerating its evolution towards intelligence and multi-domain fusion, but intra-visual range confrontation is still a key scenario due to electromagnetic interference, stealth technology limitations and tactical deception, and the high dynamics and uncertainty of the confrontation environment poses harsh challenges to the real-time and adaptive nature of threat assessment. Existing research focuses on multi-attribute decision-making methods, focusing on indicator screening, weight allocation and threat ranking [1].

First, indicator screening: traditional studies mostly rely on expert experience [2-3] or statistical analysis (e.g., principal component analysis [4-5], random forest [6-7]), but the former is vulnerable to subjective bias, and the latter is difficult to circumvent the interference of correlation among indicators. In recent years, association rule mining (e.g., Apriori algorithm [8]) and hybrid methods (e.g., gray principal component

S. M. Ghadiri et al. (eds.), *Proceedings of the 2025 4th International Conference on Engineering Management and Information Science (EMIS 2025)*, Advances in Computer Science Research 121,
https://doi.org/10.2991/978-94-6463-736-6_32

analysis [9]) have been introduced in an attempt to enhance the efficiency of indicator screening through the synergistic optimization of subjective and objective factors or to reconfigure the target threat assessment system, but both of them are difficult to adapt to the differentiated needs of threat indicators in different confrontation situations. Qualitative indicators are often described by the scale method [10] or fuzzy language [11], but the ability to portray fuzzy information is limited; quantitative indicators are extended from exact numbers to interval numbers, triangular fuzzy numbers, and other forms of uncertainty expression. Recent studies have tried to apply higher-order fuzzy sets (e.g., intuitionistic fuzzy sets [12], Vague sets [13]) to metrics modeling, and explored the multilingual conversion mechanism to enhance information completeness. However, the fusion of heterogeneous information from multiple sources in a complex battlefield is still biased, resulting in insufficient adaptation of threat assessment results to the dynamic environment.

Secondly, weight allocation: single weight method (such as hierarchical analysis [14], entropy weight method [15]) focuses on subjective experience or objective data, respectively, and exists one-sidedness; the combination of weight methods (such as linear weighting [16], product and normalization method [17]) can alleviate the defects of a single method, but the dynamic coupling mechanism of the weights lacks the mapping support of the adversarial posture.

Third, threat ranking: single-theory approaches based on classic models such as TOPSIS and VIKOR are prone to one-sided results, while multi-theory combinations (e.g., the integration of gray correlation method and TOPSIS [18], and the combination of prospect theory and variable-weight theory [19]) enhance the scientificity by complementing each other's strengths. The introduction of three-branch decision theory [20-21] further promotes the integration process of classification and ranking.

Aiming at the above problems, we propose an air target threat assessment method based on interval two-type fuzzy optimal worst method, which integrates interval two-type fuzzy set and optimal worst decision theory to enhance the modeling and reasoning ability of high-order uncertain information; and constructs a dynamic mapping mechanism of “situation typical style - threat indicator weight” to break through the constraints of the static weights on the evolution of confrontation posture. Experiments show that the method can significantly improve the dynamic adaptability of threat ranking and provide more robust quantitative support for intelligent collaborative decision making in air countermeasures.

2 Air Target Threat Assessment Indicator System

2.1 Establishment of a system of indicators for threat assessment of air targets

Based on the characteristics of dogfight the threat assessment index system is established from the static and dynamic capabilities of the aircraft, specifically including angle threat, distance threat, velocity and air combat capability threat, as shown in Figure 1. The above threats are quantified according to the formula given in the literature, and the specific formula and description of the quantification refer to the literature [9].

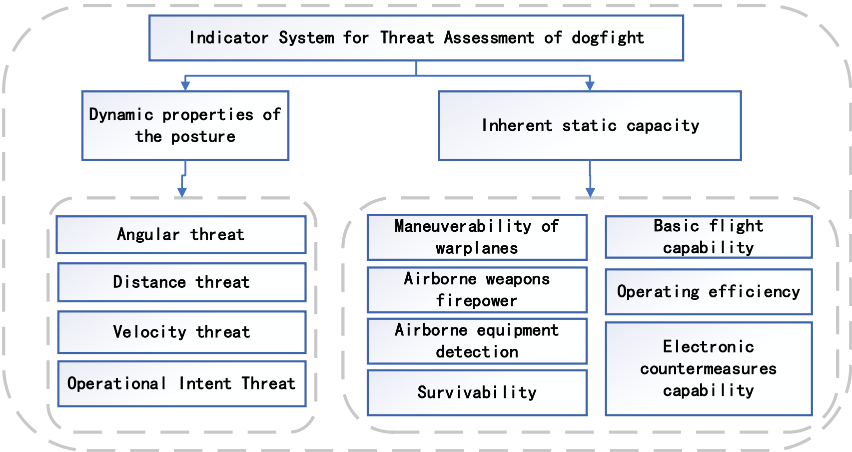


Fig. 1. Air target threat assessment indicator system

2.2 An Expert Reasoning-Based Approach to Air Combat Intent Recognition

In the existing research, the quantification of confrontation intent mostly relies on the direct definition of static parameters or a single posture indicator, whose limitation is that it fails to fully integrate the correlation characteristics of multi-source heterogeneous data in the dynamic confrontation environment, and lacks the systematic integration of the expert's empirical knowledge system. Based on this, this section adopts an improved method of confrontation intent recognition based on multidimensional posture features and expert reasoning, and the following is the relationship between different state parameters and confrontation intent based on expert experience [22], as shown in Tables 1, 2, and 3:

Table 1. Relationship between target distance and confrontation intent.

Target distance/km	Most likely confrontation intent	Unlikely confrontation intent
<100	Penetration	Attack
100-300	Attack	Feint
300-500	Detect	Attack
>500	Retreat	Detect

Table 2. Relationship between target velocity and confrontation intent

Target velocity/km/h	Most likely confrontation intent	Unlikely confrontation intent
600-850	Detect	Penetration
850-950	Penetration	Detect
950-1250	Feint	Detect
1250-1470	Attack	Retreat

Table 3. Relationship between target heading angle and confrontation intent

Target heading angle/°	Most likely confrontation intent	Unlikely confrontation intent
0-20	Penetration	Attack
20-60	Attack	Penetration
60-90	Detect	Attack
90-180	Retreat	Detect

The labeling codes for the five enemy target combat intent types are shown in Figure 2.

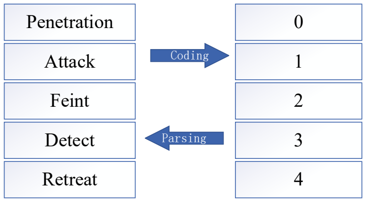


Fig. 2. Air Combat Intent Coding and Pattern Parsing

Since it is a one-on-one dogfight as the background task, the enemy's air combat intent is the main concern, and the goal of our study is to recognize the enemy's intent and adjust our own tactics accordingly, therefore, the adversarial intent recognition result evaluation function is shown in Equation (1).

$$S_{intention}\begin{cases}0.8 & , \quad I=0\\0.7 & , \quad I=1\\0.3 & , \quad I=2\\0.5 & , \quad I=3\\0.2 & , \quad I=4\end{cases} \tag{1}$$

3 A dynamic adaptation method for fuzzy weights based on posture classification

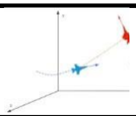
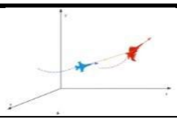
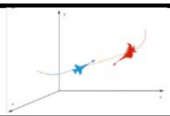
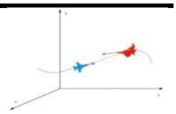
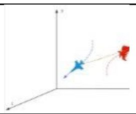
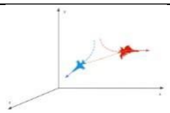
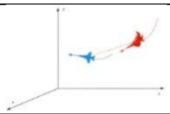
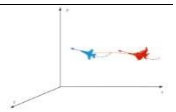
3.1 Classification of Typical Styles of Airborne Confrontation Posture

During air confrontation, the air confrontation postures are usually categorized into the following four typical styles based on the relative positions and velocity directions of the two sides [23]: trailing, being trailed, head-on, and back-off. Further considering the relative angle differences between the two sides, the above typical styles are expanded to 8 categories. For each type of typical style, a triad including target azimuth q^R, target entry angle q^B and deflection flag position f is used to describe it, as shown in Equation 2:

$$S=\{S_i=f(q^R,q^B,f)\} \tag{2}$$

Where $f=sign(q^R)sign(q^B)$. A schematic of the typical style of the posture and the corresponding parameter characteristics are shown in Table 4.

Table 4. Typical Air Confrontation Posture Style

Typical styles				
Parameter characteristics	$0 \le \lvert q^B \rvert < \pi/2, 0 \le \lvert q^R \rvert \le \pi/2$		$0 \le \lvert q^B \rvert < \pi/2, \pi/2 \le \lvert q^R \rvert \le \pi$	
	$f < 0$	$f \ge 0$	$f < 0$	$f \ge 0$
Typical styles				
Parameter characteristics	$\pi/2 \le \lvert q^B \rvert < \pi, 0 \le \lvert q^R \rvert \le \pi/2$		$\pi/2 \le \lvert q^B \rvert < \pi, \pi/2 \le \lvert q^R \rvert \le \pi$	
	$f < 0$	$f \ge 0$	$f < 0$	$f \ge 0$

3.2 IT2F-BWM based fuzzy weight dynamic adaptation approach

In the field of threat modeling, the dynamic characteristics of situational parameters (e.g., the continuous time-varying characteristics of target azimuth, the nonlinear mapping of missile effective attack area and relative displacement) tend to present dynamic fuzzy characteristics, and the multivariate coupling characteristics of enemy tactical intentions make the traditional weight allocation model face significant limitations. The interval two-type fuzzy system (IT2FS), by virtue of its unique two-tier hierarchical affiliation architecture - the primary affiliation function depicts the fuzzy characteristics within a single element, and the secondary affiliation function characterizes the cognitive differences in group decision-making - shows stronger adaptability in dealing with the dynamic fuzzy boundary problems of air combat situations. By constructing a binary comparison matrix between the optimal and the inferior criteria, the best-worst criterion analysis method (BWM) streamlines the n(n-1) comparisons required by the traditional method to 2n-3, which not only effectively controls the cumulative effect of subjective cognitive bias, but also significantly improves the time efficiency of the computation. After the theoretical integration of BWM and IT2FS, the improved IT2F-BWM framework is able to aggregate the interval fuzzy cognition of the expert group under the premise of maintaining the reasonableness of weight distribution, which effectively solves the inherent problem of the traditional hierarchical analysis method (AHP) that it is difficult to adapt to real-time decision-making on the battlefield due to the explosion of the dimension of the operation. Combining the above technical features, this paper proposes an evaluation model based on interval type two fuzzy best and worst method (IT2F-BWM), and its algorithmic implementation process can be decomposed into the following steps:

Step1: Based on air countermeasures data analysis and expert experience., determine the most significant indicator A_B^m and the weakest indicator A_W^m that have the most significant impact on the posture among the n indicators under the m air combat confrontation posture typical style.

Step2: According to the relative importance of indicators and interval type 2 fuzzy transformation criteria in the literature [26], determine the importance of indicators compared to other indicators and construct the comparison vector BTO:

$$BTO = \left(\widetilde{P_{m,B1}}, \widetilde{P_{m,B2}}, \dots, \widetilde{P_{m,Bn}}\right) \tag{3}$$

Step3: Determine the importance of the other indicators compared to u and construct a comparison vector OTW:

$$OTW = \left(\widetilde{P_{m,1W}}, \widetilde{P_{m,2W}}, \dots, \widetilde{P_{m,mW}}\right)^T \tag{4}$$

Step4: Construct a constrained optimization model for indicator weights:

Assume that the optimal interval two-type fuzzy weighting result for each posture indicator under the m[th] classical style of adversarial typical style is as follows:

$$\widetilde{\omega}_{m,i} = \begin{bmatrix} \left(\omega^L_{m,i1}, \omega^L_{m,i2}, \omega^L_{m,i3}, \omega^L_{m,i4}; H^L_{m,i1}, H^L_{m,i2}\right) \\ \left(\omega^U_{m,i1}, \omega^U_{m,i2}, \omega^U_{m,i3}, \omega^U_{m,i4}; H^U_{m,i1}, H^U_{m,i2}\right) \end{bmatrix} \tag{5}$$

Where i=1,2...n. At the same time, let the weights of the posture indicators $A^m_B$and A^m_W be $\widetilde{\omega}_{m,B}$ and $\widetilde{\omega}_{m,W}$, respectively. in order to ensure the consistency of the weighting results, the problem of solving the optimal weights of the posture indicators can be regarded as: minimizing the maximum absolute gap value $\tilde{\delta}^*_m$ in $|\widetilde{\omega}_{m,B} - \widetilde{\omega}_{m,i} * \tilde{P}_{m,Bi}|$and $|\widetilde{\omega}_{m,i} - \widetilde{\omega}_{m,W} * \tilde{P}_{m,iW}|$. thus, the constrained optimization model for solving the weights of the posture indicators is established as shown in Eq. (6).

$$\min \tilde{\delta}^*_m$$

$$s.t.\begin{cases} |\omega^L_{m,B1} - \omega^L_{m,i1} * \omega^L_{m,Bi1}| \le \tilde{\delta}^*_m, |\omega^L_{m,B2} - \omega^L_{m,i2} * \omega^L_{m,Bi2}| \le \tilde{\delta}^*_m, \\ |\omega^L_{m,B3} - \omega^L_{m,i3} * \omega^L_{m,Bi3}| \le \tilde{\delta}^*_m, |\omega^L_{m,B4} - \omega^L_{m,i4} * \omega^L_{m,Bi4}| \le \tilde{\delta}^*_m, \\ |\omega^U_{m,B1} - \omega^U_{m,i1} * \omega^U_{m,Bi1}| \le \tilde{\delta}^*_m, |\omega^U_{m,B2} - \omega^U_{m,i2} * \omega^U_{m,Bi2}| \le \tilde{\delta}^*_m, \\ |\omega^U_{m,B3} - \omega^U_{m,i3} * \omega^U_{m,Bi3}| \le \tilde{\delta}^*_m, |\omega^U_{m,B4} - \omega^U_{m,i4} * \omega^U_{m,Bi4}| \le \tilde{\delta}^*_m, \\ |\omega^L_{m,i1} - \omega^L_{m,W1} * \omega^L_{m,iW1}| \le \tilde{\delta}^*_m, |\omega^L_{m,i2} - \omega^L_{m,W2} * \omega^L_{m,iW2}| \le \tilde{\delta}^*_m, \\ |\omega^L_{m,i3} - \omega^L_{m,W3} * \omega^L_{m,iW3}| \le \tilde{\delta}^*_m, |\omega^L_{m,i4} - \omega^L_{m,W4} * \omega^L_{m,iW4}| \le \tilde{\delta}^*_m, \\ |\omega^U_{m,i1} - \omega^U_{m,W1} * \omega^U_{m,iW1}| \le \tilde{\delta}^*_m, |\omega^U_{m,i2} - \omega^U_{m,W2} * \omega^U_{m,iW2}| \le \tilde{\delta}^*_m, \\ |\omega^U_{m,i3} - \omega^U_{m,W3} * \omega^U_{m,iW3}| \le \tilde{\delta}^*_m, |\omega^U_{m,i4} - \omega^U_{m,W4} * \omega^U_{m,iW4}| \le \tilde{\delta}^*_m, \\ \sum_{i=1}^n D\left(\widetilde{\omega}_{m,i}\right) = 1 \\ \omega^U_{m,i1} \le \omega^L_{m,i1}, \omega^L_{m,i4} \le \omega^U_{m,i4}, \omega^L_{m,i1} \le \omega^L_{m,i2} \le \omega^L_{m,i3} \le \omega^L_{m,i4}, \\ \omega^U_{m,i1} \le \omega^U_{m,i2} \le \omega^U_{m,i3} \le \omega^U_{m,i4}, \omega^U_{m,i1} \ge 0 (i = 1,2,\dots,n) \end{cases} \tag{6}$$

Step5: After the interval two-type fuzzy weights of the posture assessment indicators are obtained by solving according to Equation (6), the final weight results are obtained by defuzzification of the fuzzy weight results using Equation (7).

$$D(\widetilde{\omega}_{m,i}) = \frac{(\omega_{m,i4}^{L}-\omega_{m,i1}^{L})+(H_{m,i,1}^{L}\omega_{m,i2}^{L}-\omega_{m,i1}^{L})}{8} + \frac{(H_{m,i,2}^{L}\omega_{m,i3}^{L}-\omega_{m,i1}^{L})}{8} + \frac{\omega_{m,i1}^{L}+\omega_{m,i1}^{U}}{2} + \frac{(\omega_{m,i4}^{U}-\omega_{m,i1}^{U})+(H_{m,i,1}^{U}\omega_{m,i2}^{U}-\omega_{m,i1}^{U})}{8} + \frac{(H_{m,i,2}^{U}\omega_{m,i3}^{U}-\omega_{m,i1}^{U})}{8} \tag{7}$$

3.3 Weight dynamic adaptation and threat assessment of airborne targets

According to the IT2F-BWM calculation steps, the ambiguous weight of IT2F is shown in Table 5 and the mapping relationship of "typical posture style - threat indicator weight" is obtained for the refined typical posture, as shown in Table 6:

Table 5. Partial interval type II fuzzy weighting results

Posture S_i	indicator	Optimal interval type II fuzzy weighting results
S_1	Velocity	[(0.50,0.55,0.60,0.65;0.9,1.0),(0.52,0.56,0.58,0.63;0.8,0.9)][(0.50,0.55,0.60,0.65;0.9,1.0),(0.52,0.56,0.58,0.63;0.8,0.9)]
	Angle	[(0.08,0.10,0.12,0.15;0.8,0.9),(0.09,0.11,0.13,0.14;0.7,0.8)][(0.08,0.10,0.12,0.15;0.8,0.9),(0.09,0.11,0.13,0.14;0.7,0.8)]
	Distance	[(0.10,0.12,0.14,0.16;0.7,0.8),(0.11,0.13,0.15,0.17;0.6,0.7)][(0.10,0.12,0.14,0.16;0.7,0.8),(0.11,0.13,0.15,0.17;0.6,0.7)]
	Capability	[(0.04,0.05,0.06,0.07;0.6,0.7),(0.045,0.055,0.065,0.075;0.5,0.6)][(0.04,0.05,0.06,0.07;0.6,0.7),(0.045,0.055,0.065,0.075;0.5,0.6)]
	Intention	[(0.01,0.02,0.03,0.04;0.5,0.6),(0.015,0.025,0.035,0.045;0.4,0.5)][(0.01,0.02,0.03,0.04;0.5,0.6),(0.015,0.025,0.035,0.045;0.4,0.5)]
…	…	…

Table 6. "Typical posture style-threat indicator weights" mapping relationship

Posture S_i	Angle	Velocity	Distance	Capability	Intention
S_1	0.11	0.57	0.13	0.06	0.03
S_2	0.68	0.13	0.11	0.04	0.03
S_3	0.62	0.07	0.15	0.05	0.04
S_4	0.72	0.09	0.08	0.05	0.03
S_5	0.65	0.06	0.13	0.06	0.04
S_6	0.77	0.07	0.10	0.04	0.03
S_7	0.69	0.08	0.11	0.05	0.04
S_8	0.81	0.06	0.09	0.04	0.03

In the process of comprehensive situational threat assessment, firstly, real-time classification judgment of typical styles of posture is carried out according to the current flight data, and then posture indicator weight matching is carried out in accordance with the mapping relationship in Table 6, and finally, the following formula is used to aggregate each posture indicator, which dynamically presents the influence of each posture indicator on the comprehensive threat changes.

$$S = \omega_{i,1}S_{intention} + \omega_{i,1}S_{\text{angle}} + \omega_{i,1}S_{\text{velocity}} + \omega_{i,1}S_{\text{distance}} + \omega_{i,1}S_{\text{capability}} \tag{8}$$

where $\omega_{i,j}(i = 1,2, \dots ,8; j = 1,2, \dots ,5)$denotes the weight of the j^{th}threat indicator under the typical style of the i^{th} type of posture.

4 Experimental analysis

4.1 Case analysis

Assuming that in an air battle, we encounter four enemy aircraft (F-16C, F-15E, F-5E), the speed of our carrier aircraft is 320m/s, the heading angle is assumed to be 0° (due north), the maximum range of airborne missiles is 60km, and the enemy aircraft is within the detection and tracking range of our airborne fire-control radar, and the maximum radar detection range of the two sides of the enemy is 120km.The detailed situational information of the enemy aircraft is shown in Table 7.

Table 7. Enemy aircraft posture data

Time	Target	Models	$q^B/(°)$	$q^R/(°)$	r/km	v/(m/s)	Missile range
t-1	1	F-16C	80	-45	80	300	60
	2	F-16C	45	-45	70	325	80
	3	F-5E	-60	80	60	320	50
	4	F-15E	-45	15	60	330	70
t	1	F-16C	78	-52	76	316	60
	2	F-16C	51	-47	74	318	80
	3	F-5E	-57	86	65	332	50
	4	F-15E	-49	21	58	346	70

By reference [9] calculate the angle threat S_{angle} , distance threat $S_{distance}$, velocity threat $S_{velocity}$, air combat capability threat $S_{\text{capability}}$, and according to equation 1 calculate the operational intent threat $S_{intention}$, the results of the determination of operational intent, the results of the typical posture corresponding to the results are shown in Table 8, the calculation of the threat value of the target's various indicators as well as the relative air combat capability are shown in Table 9:

Table 8. Typical Posture and Operational Intent Analysis Results

Time	Target	Models	Posture	Intention
t-1	1	F-16C	S_1	0
	2	F-16C	S_1	1
	3	F-5E	S_1	3
	4	F-15E	S_1	1
t	1	F-16C	S_1	0
	2	F-16C	S_1	1
	3	F-5E	S_1	3
	4	F-15E	S_1	1

Table 9. Indicator threat value

Target	1	2	3	4
$S_{\text{capability}}$	0.85	0.85	0.41	1.00
S_{angle}	0.36	0.27	0.40	0.19
$S_{distance}$	0.50	1.00	0.50	0.80
$S_{velocity}$	0.4875	0.4938	0.5375	0.5813
$S_{intention}$	0.80	0.70	0.50	0.70

According to Table 5 and equation (8) the final threat value of each target can be calculated and compared with the results in literature [24,25], literature [16], and literature [9] as shown in Table 10:

Table 10. Comparison of four methods

Target	IT2F-BWM	Rank	GC	Rank	GPCA [9]	Rank	[24-25]	[16]
1	0.41695	2	0.5388	1	0.7184	2	2	2
2	0.428028	1	0.4419	4	-0.3096	3	1	3
3	0.38535	3	0.5149	2	0.8467	1	4	1
4	0.378178	4	0.4950	3	-1.2555	4	3	4

The experimental results show that the differences in target threat ranking between the different methods are mainly due to the differences in the weight allocation methods. IT2F-BWM adopts a dynamic weight adaptation mechanism, whereas the gray principal component, gray correlation, literature 24-25 and literature 16 methods adopt static weights, which are less adaptable in the complex battlefield environment. In addition, the IT2F-BWM and gray principal component methods consider the operational intent, while the literature 16 does not include this factor, resulting in the threat ranking of some targets deviating from the actual tactical needs.

The experimental data show that the IT2F-BWM assessment results are Target 2>1>3>4, in which Target 2 (attack) has the highest threat and Target 4 (attack) has the lowest. This method can effectively improve the threat assessment of attack targets and reasonably distinguish low threat targets. The gray correlation method, on the other hand, assesses 1>3>4>2, incorrectly rating target 1 (penetration) as the highest threat and target 2 (attack) as the lowest, reflecting that the static weighting method fails to adequately consider the operational intent, resulting in low assessment of actual attack targets.

The gray principal component method was ranked 3>1>2>4. Although the method considers operational intent, it may amplify the effects of non-critical metrics due to the use of static weights.

Literature 24-25 The method's ranking of 2>1>4>3 is close to that of IT2F-BWM, suggesting that it is able to recognize the high threat of attacking targets to some extent. However, it is difficult to adapt to the change of battlefield situation due to the static weights, and the evaluation results lack flexibility in different situations.

From a comprehensive perspective, IT2F-BWM can dynamically adjust the threat assessment weights by combining the operational intent, tactical background and movement characteristics through the dynamic weight adaptation mechanism, so that the assessment results can better meet the battlefield requirements.

4.2 Computational complexity, real-time analysis

Compared with other methods, the IT2F-BWM method has significant advantages in terms of computational complexity and real-time performance. In the initial stage, the method determines the most and least important indicators in the context through expert experience and calculates the comparison vector, then constructs Typical posture style-threat indicator weights mapping relationship through calculation and calculates the threat value by directly checking the table in the subsequent assessment, which avoids real-time calculation of weight distribution and greatly improves the computational efficiency.

In contrast, other methods still need to perform real-time calculations for each assessment, such as the gray principal component method, which requires feature decomposition and contribution rate calculation, and the gray correlation method, which requires calculating the gray correlation between the target and the ideal target, whereas IT2F-BWM only needs to calculate the threat value according to the mapping table, which reduces redundant calculations and improves the assessment speed.

In addition, IT2F-BWM only relies on expert experience in the mapping relationship establishment phase and can run independently afterwards, while methods such as gray principal components and gray correlation always rely on real-time data calculation, which may affect the stability of the assessment when the data fluctuates greatly. Therefore, IT2F-BWM is suitable for high-dynamic air combat scenarios, which ensures the accuracy of the assessment while reducing the consumption of computational resources and improving the real-time and stability of the threat assessment.

5 Conclusions

The dynamic game characteristic of air confrontation requires that the weights need to be adjusted in real time with the enemy-us interaction. The IT2F-BWM-based airborne target threat assessment method proposed in this paper divides the air confrontation mode through typical posture styles, and uses IT2F to characterize the uncertainty in the weights, and BWM to construct comparison vectors to adjust the correlation between the indicators and other indicators, and to solve the weight values of the indicators corresponding to different postures, so as to realize the dynamic adaption of the weights, which is more in line with the needs of actual combat. At the same time, the identification of operational intent is correlated with other threat indicators, and expert experience is used to drive the identification of operational intent, which greatly saves the computational volume of the whole model and meets the requirements of real-time threat assessment.

Finally, the method in this paper provides a theoretical framework that balances ambiguity, dynamics, and real-time for threat assessment of air confrontation targets, improves the tactical credibility of threat assessment, and provides highly robust theoretical support for real-time decision-making in air confrontation. Future research can be further extended to the field of multi-intelligence body collaborative threat assessment, and explore the integration mechanism of deep learning and IT2F-BWM to cope with the real-time processing requirements of high-dimensional heterogeneous battlefield data.

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