Research Article

Target Tactical Intention Recognition in Multiaircraft Cooperative Air Combat

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Accuracy identifying the tactical intention of the target can facilitate the prediction of the opponent’s behavior and improve the efficiency of collaborative decision. We have observed that traditional methods could achieve high recognition rate on conventional tactical intent. Nevertheless, their performance would deteriorate seriously when recognizing cooperative tactical intention in multiaircraft air combat environment. The main reason resides on key features that are difficult to extract for traditional methods. To this end, this paper proposes a novel approach to recognizing tactical intention of multiaircraft cooperative air combat. Specifically, we employ support vector machine (SVM) to forecast the attack intention based on 19 low correlation features. The purpose of the employment of SVM is to avoid local optimization and reduce data dimension. Moreover, we use three models, i.e., dynamic Bayesian network (DBN), radar model, and threat assessment model to extract crucial information regarding maneuver occupancy, silent penetration, and attack tendency. The extracted information would make great contribution to the recognition accuracy of six types of cooperative tactics. Finally, we learn a decision tree model on train samples processed by above two phases to classify different tactical intention. In order to verify the effectiveness of the proposed method, we use data sets from a loop simulation platform. The experimental results have approved the superiority of our method via the comparison to several baseline methods with respect to recognition rate and efficiency. In addition, we underline that our method also performs well on incomplete and uncertain information.

1. Introduction

Command and control system is an indispensable part of modern warfare. It is composed of command, control, communication, computer, and intelligence, which is called C4I for short. The rapid development of modern air combat complicates the coordinated fighter confrontation, so the requirement for an efficient command system is increasing. This research can effectively complete the information fusion of C4I data and has good application prospects in both the near future and the long-term analysis. Especially in the background of multiaircraft cooperative air combat, the effective identification of the target’s tactical intention is of great significance to the follow-up command and control. In the field of unmanned aerial vehicle (UAV) air combat, it can access the front-end of the decision system to guide UAV operations [1]. In the field of manned aerial warfare, it can provide the target tactical intention to the pilots to improve the efficiency of pilots’ decision-making, thus, achieving earlier discovery, decision-making, and attack than the enemy [2].

In recent years, scholars have built different models to study the problem of intent recognition in different fields. In the field of air-combat target intention recognition, paper [3] comprehensively analyses the correlation between track and tactics and uses a deep neural network to identify the operational intent of a single air target. In [4], an air target intention prediction method based on information entropy is studied, which achieves effective recognition of common operational intentions. In [5], a prediction model of air combat target intention based on the LSTM network using
incomplete information is presented. An adaptive moment estimation (Adam) optimization algorithm is used to speed up the training of the target intention prediction model, which effectively prevents the problem of local optimization. Although the above methods have a good effect on target conventional tactical intention recognition, these methods cannot effectively solve the problem of cooperative tactical intention recognition in a complex air-combat environment. Additionally, adding features of different linearity and correlation degrees to the classifier will reduce the recognition rate of some tags, which will affect the interpretability of the model. In the field of vehicle driver braking intention recognition, different types of neural networks are used to improve the accuracy of intention recognition by learning cumulative sample data [6, 7]. SVM is used to extract features of low correlation parameters, and then the extracted results and high correlation features are used for data mining, which further improves the accuracy of vehicle driver braking intention recognition [8]. In the field of user intention recognition, paper [9] proposes an autoencoder-enabled and k-means clustering-based (AKMC) method to identify potential buyers, which achieves a model accuracy of 82%, outperforming other traditional machine learning methods. Paper [10] proposes a Bi-Directional Grid Long-Short Term Memory RNN framework for enhancing the efficiency of user intention identification. By analyzing the above research results comprehensively, scholars generally use machine learning to solve the problem of intention recognition. The correlation and completeness of the selected parameter features are the key factors that affect the accuracy of the recognition results. These results have a good reference for the method proposed in this paper.

Cooperative tactical intention recognition requires effective handling of the coupling between the independent intentions of the fighters in the formation. The handling of coupling relationships is common in the field of identification, and there are usually two solutions. Scheme 1 first extracts the coupling features of different units and then takes them together with other directly available features as the input of the classifier, to obtain the recognition results of each unit containing coupling features [11–13]. Scheme 2 first obtains the independent recognition results for each cell, then infers the coupling characteristics based on the association of these results, and finally feeds the resulting coupling features back to the classifier to improve the accuracy of the recognition results [14]. The two scenarios seem to just step in a different order, but in fact, they differ greatly in modeling difficulty and generality. At present, the traditional research does not consider the cooperative characteristics of multi-aircraft air combat. Only some conventional tactical intentions such as an attack, lock-on, electronic countermeasures, patrol, support, and retreat can be identified. How to make accurate and effective identification of tactical intention in cooperative air combat is the focus of this paper.

To meet the needs of actual combat, we study the above problems and establish a general target tactical intention recognition model in multi-aircraft cooperative air combat. In the first step, an SVM classifier is constructed to extract attack intent from the features of different linearity and correlation degrees, which can reduce the dimension of many low correlation features. In the second step, we select the first scheme of the previous paragraph and design three feature extraction methods to distill higher-level collaborative tactics features from a large number of primary features. Finally, based on the features extracted from the above steps, air combat simulation samples are used to train the decision tree model as a tactical intent classifier. We expect that the results of this study will inspire other scientists and produce more research to rewrite the rules of air combat.

Cooperative tactical recognition can lay a solid foundation for cooperative decision theory and pave the way for further development of effective methods of identifying and recognizing the air combat or air traffic participants’ intentions. In summary, the contributions of this paper are as follows:

(i) For the first time in the field of intention recognition, we have solved the problem of multi-aircraft cooperative air combat tactical intention recognition and expanded the tactical database to 12 categories. More importantly, cooperative tactics that can cause heavy losses, such as silent penetration and over the horizon suppression, can be recognized to improve the survival rate of fighters

(ii) The accuracy of single target intention recognition is significantly higher than that of similar algorithms, reaching 0.9893. On the premise of reaching the peak performance of the model, the number of training samples required by this method is far less than the deep neural network algorithm

(iii) This method has a clear structure and strong interpretability. Its single-cycle operation speed reaches milliseconds and the convergence speed is fast, which can meet the real-time requirements of air confrontation. The model can operate stably with uncertain and incomplete information. The above three points are indispensable for military applications

(iv) This method conforms to the Multiagent Hierarchical Policy (MAHP) theory. The effectiveness of the cooperative tactical decision can be improved by inputting the recognition results as evidence information into the decision model. In addition, SVM and C4.5 are used to build learners to reduce the dependence on prior knowledge

2. General Technology Scheme

In modern air warfare, fighters usually perform combat missions information, with corresponding tactics laid out through the command system. These tactics are time-varying and have different characteristics, which brings a lot of uncertainty to target tactical intention recognition [15]. To improve accuracy, more parameters are integrated to build the recognition model. The following parameters will be used: flight dynamics parameters, such as speed and
normal overload; radar system parameters, such as radar power and RCS value; weapon system parameters, such as missile mass and fuel-specific impulse; and space occupancy parameters, such as distance and heading angle. These are low correlation parameters related to air combat intelligence information. The space occupancy situation of the target and my aircraft is shown in Figure 1. There are also some relatively high correlation parameters in the parameter library, such as electronic countermeasure (ECM) status, radar mode, and system support status, which are related to information situation. Parameters are often referred to as features in the field of identification.

The general technical scheme of this article consists of two parts. The first part reduces the dimension of low correlation parameters and identifies the common tactical intent. The second part provides three feature extraction methods for collaborative tactical intent using highly sensitive features. Figure 2 is the general technical scheme block diagram for target tactical intention recognition in multiaircraft cooperative air combat.

The premise of identifying the cooperative tactical intent of multiple aircraft is to identify the intent of a single aircraft. Predicting the attacking intent is the key to conventional tactical intent inference for a single aircraft, which is defined as determining whether the target is currently attacking me. In this paper, SVM is used to extract attacking intent from low-correlation air combat situation parameters to reduce the dimension of low-correlation characteristics and improve the recognition effect of single-aircraft countermeasure tactical intent. SVM is a statistical learning method that can effectively solve small sample nonlinear problems. It does not appear local minimization when solving classification problems based on convex functions, and the model is more stable. In addition, SVM has an excellent small sample performance [16, 17]. If we are only satisfied with identifying conventional tactical intentions, it is sufficient to use three high-correlation and attack intent features. The conventional tactical intent can be obtained by setting up an appropriate classifier. We choose to build a tactical intent classifier using a decision tree.

We hope to further identify the characteristics of cooperative tactical intent. In a multiaircraft cooperative air combat environment, the diversity of tactical intentions increases. Even for common attack missions, different attack modes will be selected according to the type of fighter and the amount carried. How to extract features without breaking the generality becomes the focus of our research. The third paragraph of the introduction describes the system identification schemes with coupling relationships. In this paper, the first scheme is selected. The second scheme is simpler and easier to understand, but different reasoning rules need to be designed in the face of a different number of objectives, and generality cannot meet the needs. For example, refer to chapter 6 of this paper, the mathematical simulation of air combat between four enemy fighters and two of our fighters. After identifying the general tactical intent, it is easier to infer the cooperative tactical intent by establishing a state transition matrix based on the correlation between the tactics. If at the next moment an enemy plane is shot down to form a three-to-two battle, it is clear that the state transition matrix needs to be rebuilt. Temporarily building solutions can be fatal for air combat. Therefore, based on one-on-one countermeasure tactical intention recognition, several feature extraction algorithms are designed based on expert knowledge to achieve the recognition of cooperative tactical intent. Although feature extraction methods need to be designed based on expert experience, the generality of cooperative tactical intention recognition methods has been improved.

In this section, the following algorithms are used for collaborative tactical intent feature extraction.

- Maneuvering occupancy feature extraction based on DBN. The maneuvering occupancy feature is highly sensitive and can improve the recognition rate of cooperative tactical intent. DBN is a time-sequence Bayesian network, which can effectively improve the accuracy of fighter maneuver recognition [18]. In this paper, a new network architecture is proposed to make an accurate maneuvering occupancy feature extraction.

- Silent penetration feature extraction based on radar model. Silent penetration is a special direct attack tactic, which is usually completed by multiple fighters. The radar model can determine the operating range of airborne radar [19], which is helpful to determine whether the enemy aircraft is in the silent penetration state.

- Enemy attack feature extraction based on threat assessment. Threat assessment can help pilots to determine the attack ability of targets [20]. Based on threat assessment, we design a feature extraction method to infer the
enemy’s attack tendentiousness to identify the main enemy attack targets.

After the above features are extracted, we use the C4.5 decision tree to learn classification rules from all the features to realize the reasoning of target tactical intention in multiaircraft cooperative air combat. The decision tree is a supervised learning algorithm based on information entropy. Some trees can tolerate missing values [21–23]. After the training of the decision tree, the target tactical intention recognition model is generated, which can effectively identify the cooperative tactical intention.

### 3. Attack Intention Reasoning Based on SVM

Accurate recognition of conventional tactical intent is the basis of cooperative tactical intention recognition. The most important thing to identify the conventional tactical intent is to get the target’s attack intent, which is a typical nonlinear binary classification problem. The main goal of this section is to extract the attacking intent from all global low-correlation features. The identification result as a feature can be quantified as having an attacking intent or not. The samples are divided into a training set and a test set. The training set is used to generate the desired model, and the test set is used to evaluate the model performance. The entire training and testing process is shown in Figure 3.

**Step 1.** Low-correlation features preprocessing. Global low-correlation features include target speed, my speed, target acceleration, target normal overload, missile weight, missile propellant weight, propellant specific impulse, energy loss factor, radar main lobe performance constant, RCS, noise power, clutter power, target height, my altitude, target azimuth, target approaching angle, target course angle, approach speed, and the relative distance between two sides. The features total 19 dimensions. The existence of nonstandard data

![Figure 2: The general technical scheme block diagram for target tactical intention recognition in multiaircraft cooperative air combat.](image)

![Figure 3: Flow chart of training and testing. There are four steps to generate the SVM model. Inside the left box is the training process, corresponding to steps 1–3 below. Inside the right box is the test process, corresponding to Step4 below.](image)
During training usually reduces the fitness of the model. Therefore, it is necessary to standardize the samples before training. This paper chooses the Z-score method to process data. It unifies the orders of magnitude of different data into the same order. Z-score is defined as:

$$
z(D) = \frac{x - \mu}{\sigma} = \frac{x - \mu}{\sqrt{1/n \sum_{i=1}^{N} (x_i - \mu)^2}}.
$$

Among them, $x$ is the feature observation value, $\mu$ is the total sample mean, and $\sigma$ is the sample standard deviation. In previous experiments, the authors found that algorithms dependent on sample spacing are sensitive to magnitude differences in features. This problem happens to be eliminated when Z-score standardization is used. In addition, this method can improve the convergence speed of the model and make the model have better performance when facing fewer samples.

Before inputting the normalized features into the SVM module, we performed a denoising process on the data. The classification principle of SVM is based on sample spacing, so it is particularly sensitive to noise data, so data cleaning is necessary. The sample already has a population standard deviation at the standardization stage, so the Gaussian denoising method can be used. Gauss distribution is one of the probability distributions of continuous random variables whose form is called a bell curve. The probability density near the mean value is much greater than that far from it. This signifies that points in the samples that are relatively far from the mean value can be considered noise. After noise removal, a standardization process needs to be performed again.

**Step 2. Hyperparameter selection based on grid search and cross-validation.** There are two hyperparameters, C and $\gamma$, respectively. Grid search is a method of searching for the optimal parameters globally. It uses a wider search range and a larger step first, then narrows the range and step gradually. If there are consecutive identical hyperparameters that can make the performance of the model optimal in a certain search, it is considered that the optimal value of the hyperparameters is found. The loop in the dashed frame on the left side of Figure 3 will now be terminated. In this paper, cross-validation is introduced based on the grid search, and the hyperparameters optimal solution selected by cross-validation will make the model have better generalization performance. Cross-validation divides the sample data into $k$ equal parts, taking one as the test set and the other $k-1$ as the training set. By testing all samples circularly, $k$ performance indexes are output and take their average value as test result. The thick grey arrow in Figure 3 indicates that the cross-validation result from the test set is input into the training set to determine whether the hyperparameters are optimal.

**Step 3. Model training.** The core idea of SVM is to map samples into a high-dimensional space through a kernel function and construct an optimal classification hyperplane in this space. This principle enables SVM to handle high-dimensional nonlinear problems.
can be used to determine the location of the optimal classified hyperplane.

\[
\min \frac{1}{2} \| \omega \| + C \sum_{i=1}^{m} \zeta_i \\
\text{s.t. } D_i (\omega^T x_i + b) \geq 1 - \zeta_i, \quad \zeta_i \geq 0.
\]  

(2)

In formula (2), \( D_i \) is the sample set, \( \omega^T x_i + b \) is the hyperplane, \( \omega \) is the normal vector of the hyperplane, and \( \zeta_i \) is the relaxation variable. It can be seen that the most critical parameter in the formula is penalty parameter \( C \), which represents the relaxation degree. Larger \( C \) have less tolerance for incorrect samples, and the fitting degree of the model will be improved. However, too large parameter may result in overfitting, which will degrade the generalization performance of the model. It can be seen that the value of \( C \) directly affects the confidence range and experience error of the learning machine.

Formula (3) introduces a Lagrange multiplier and a kernel function, which transforms Formula (2) into a quadratic programming problem [16]. Where \( \alpha_i \) is a Lagrange

\begin{table}
\centering
\caption{The definition of network nodes.}
\begin{tabular}{|l|l|l|l|}
\hline
Type & Features & State set & Node \\
\hline
Input node & Altitude trend & [Increase, unchanged, decrease] & AT \\
& Velocity trend & [Increase, unchanged, decrease] & VT \\
& Acceleration trend & [Increase, unchanged, decrease] & ART \\
& Course angle trend & [Increase, unchanged, decrease, mutation] & CAT \\
& Normal overload & {Small, medium, large} & NO \\
& Approaching speed & {High positive value, small value, high negative value} & AS \\
& Distance & {Far, near} & D \\
& Approaching angle trend & {Decrease, no decrease} & AAT \\
\hline
Intermediate node & Energy change classification & {Steady maneuver, height rise, height reduction, level flight, consume energy quickly, increase energy quickly} & COE \\
& Maneuver & {Steady level flight, accelerating level flight, decelerating level flight, left/right steady circling, left/right instantaneous circling, left/right battle turn, jump, dive, high-performance, split-S, Immelmann} & M \\
& Spatial variation & {Plumb surface, turn} & SV \\
\hline
Root node & Mobile occupancy & {Aggressive occupancy (ao), general occupancy (go), high-performance occupancy (hpo), escape (e)} & MO \\
\hline
\end{tabular}
\end{table}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{fuzzification.png}
\caption{Fuzzification of normal overload, which can be quantified as small, medium, or large.}
\end{figure}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{attack_tendency.png}
\caption{Attack tendency feature extraction process. F1-Fn represents our different fighters, and T represents the enemy fighter. The threat assessment value of each aircraft to the target is obtained through the data link. Then, rank these evaluation values to get the enemy’s attack tendency.}
\end{figure}
multiplier and \( k(x_i, x_j) \) is a kernel function. Only a small number of sample points near the hyperplane are selected, which reduces the complexity of the model when the dimension is higher.

\[
\begin{align*}
\max L(\alpha) &= \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{m} \alpha_i \alpha_j D_i D_j k(x_i, x_j), \\
\text{s.t.} \sum_{i=1}^{m} \alpha_i D_i &= 0, \\
\alpha_i &\geq 0 \quad i = 1, \ldots, m.
\end{align*}
\]

These are the two most important formulas in the basic principles of SVM. The package of SVM is very mature, so in practice we only need to adjust the hyperparameters. The most commonly used Gaussian kernel is adopted as the kernel function.

In formula (4), \( \gamma \) is another adjustable kernel function parameter in SVM. \( \gamma \) controls the range of sample points, and the larger \( \gamma \) has the stronger mapping ability. Only a small number of points selected as support vector machines can influence the model.

\[
k(x_i, x_j) = \exp \left( -\frac{||x_i - x_j||^2}{2\gamma^2} \right). \quad (4)
\]

**Table 2: Label set for cooperative tactical intention.**

| Classification | Tactical intention | Label description | Abbreviation |
|----------------|--------------------|-------------------|--------------|
| General tactical intention | Electronic countermeasure | Multiband electromagnetic suppression/deception | EC |
| | Support | Flight a long distance to a war zone | S |
| | Reconnaissance patrol | Use less force to guard airspace | RP |
| | Direct attack | Routine offense | DA |
| | Lock on | The target radar is in lock on state | LO |
| | Retreat | Quickly disengage from the current battle | RT |
| General cooperative tactical intention | Silent penetration | Turn off the radar and penetrate quickly | SP |
| | Diversion attack | Fly around to the rear of the target to attack | DVA |
| | Lure | Lure the enemy into a trap | L |
| Complex cooperative tactical intention | Cooperative attack | Cooperate with the lead aircraft to attack | CA |
| | Beyond visual range suppression | Attacking multiple targets at beyond visual range simultaneously | BS |
| | Feint | Cover up the assault intention and attack other targets | F |

**Table 3: Features of general tactical intentions.**

| Attack intent | Electronic countermeasure | Radar status | System support |
|---------------|--------------------------|--------------|----------------|
| AI            | ECM                      | RS           | SS             |

**Table 4: Features of cooperative tactical intentions.**

| General tactic | Maneuver occupancy | Silent penetration | Attack tendency |
|----------------|-------------------|-------------------|-----------------|
| GT             | MO                | PI                | TA              |

\[
P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad F1 = \frac{2 * P * R}{P + R}. \quad (5, 6)
\]

\( TP \) is the number of true positive cases, \( FP \) is the number of false positive cases, and \( FN \) is the number of false negative cases.

\( F1 \) is a more accurate and comprehensive measurement parameter that can be obtained by solving the harmonic mean of \( P \) and \( R \).

**4. Collaborative Tactical Intention Feature Extraction**

**4.1. Mobile Occupancy Feature Extraction Based on DBN**

(1) Network structure establishment

Unlike single-aircraft countermeasure, multi-aircraft cooperative countermeasure has vaster and more dynamic state space. Target mobile occupancy intention recognition based on DBN is of great significance to the confidence of recognition results, which can greatly improve the confidence of
cooperative tactical recognition. Therefore, a classifier of target maneuver occupation intention is constructed, whose recognition results can provide support for cooperative tactical intention classification. The primary features selected in this section are altitude, target speed, target acceleration, target course angle, normal overload, approach rate, relative distance, and target approaching angle. Unlike SVM, DBN model performance depends on a subjectively built network architecture. Taking the above eight features as observation nodes, according to the causal relationship between network nodes, the DBN model is constructed as shown in Figure 4. The network model is divided into three layers: the bottom layer roughly classifies the maneuvers according to the energy variation of the fighter; the second layer classifies the maneuvers from 14 types of maneuvers; the top layer identifies the type of mobile occupancy based on the spatial occupancy information. To improve the accuracy of recognition, the features of these network nodes are fuzzified. The definition of network nodes is shown in Table 1.

The input nodes contain eight preliminary features, which are preprocessed and fuzzified and are presented in the first eight rows of the table. The three intermediate nodes, COE, MD, and SV, represent the energy classification of maneuvers, the category of maneuvers, and the spatial change trend of fighters. The root node in the last row of the table is the mobile occupancy intent. The abbreviation of the feature extraction results is indicated in parentheses.

(2) Network model inference

Flight parameter changes are real-time and continuous during air combat. DBNs are affected by Markov processes, so inaccurate data in any time slice can affect the performance of the classifier for a long time. The fuzzification method is used to preprocess the air combat parameters before probability inference to reduce the inaccuracy of the parameters. After fuzzification, the continuous value parameter is discretized. In this paper, the center of gravity method is applied for fuzzification using the sigmoid membership function [24]. Figure 5 is an example of normal overload as a fuzzification variable.

Bayesian network is a directed acyclic graph, which is a chain network structure similar to a tree graph. Reasoning from any node in a network will never return to that node,
which is called chain inference. Bayesian chain inference follows the principle of conditional independence. Based on the established DBN model of mobile occupancy feature extraction, the recognition probability is calculated by chain inference according to the current time probability distribution of the leaf nodes (observation nodes). All intermediate nodes in the Bayesian network constructed in this paper are of the same parent structure, and the conditional probability

![Figure 9: Test set data for SVM. (a) To measure the performance of training samples of different sizes, the four values are accuracy, precision, recall, and F1. (b) Diagram of parameter values, C and γ are represented on the left and right coordinate axes, respectively.](image)

![Figure 10: Attack intent of the targets.](image)
distribution at the current moment is calculated based on the evidence information:

\[
P(MO_t|e_t) = P(MO_t|AV_t, VV_t, ARV_t, CAV_t, NO_t, AS_t, D_t, AAV_t) \\
= P(MO_t|AV_t) \cdot P(MO_t|VV_t) \cdot P(MO_t|ARV_t) \\
\cdot P(MO_t|CAV_t) \cdot P(MO_t|NO_t) \cdot P(MO_t|AS_t) \\
\cdot P(MO_t|D_t) \cdot P(MO_t|AAV_t).
\]  

(7)

Dynamic Bayesian network connects different variables with adjacent time slices, which is usually described as a hidden Markov process [25]. In this section, the hidden Markov process is only affected by the characteristics of the last time slice and the current moment. Using Bayesian formula, the probability distribution of mobile occupancy features can be obtained from the inference results of the previous moment and new evidence information:

\[
\begin{align*}
P(MO_{t+1}|e_{t+1}) \\ = \frac{P(e_{t+1}|MO_{t+1}) \sum_{MO_t} P(MO_t|e_t) \cdot P(MO_t|MO_{t+1})}{\sum_{MO_t} P(e_{t+1}|MO_{t+1}) \sum_{MO_t} P(MO_t|e_t) \cdot P(MO_t|MO_{t+1})}.
\end{align*}
\]

MO = \{ao, go, hpo, es\}

(8)

4.2. Silent Penetration Feature Extraction Using Radar Model. Silent penetration is defined as the target shutting down the radar to reduce the possibility of being discovered in order to achieve a sudden attack. In order to achieve the purpose of surprise attack, this kind of enemy will approach our plane or other members of the formation directly behind us in a concealed and fast manner and then turn on the radar to launch an attack when they are close to the radar locking range. For the first time, we introduced this dangerous situation into the characteristics to avoid unnecessary losses.

In this section, a radar detection range model is established to recognize the feature. The operating range of radar main lobe is usually expressed as:

\[
R^4_{\text{max}} = \frac{P_{\text{av}} G_{\text{SL}}^2 \lambda^2 \cdot \text{RCS}}{(4\pi)^3 (c + n)L},
\]  

(9)

where \(P_{\text{av}}\) is the average transmit power, \(G_{\text{SL}}\) is the antenna main lobe gain, \(\lambda\) is the wavelength, \(\text{RCS}\) is the radar cross-section of the target, \(c\) is the ground clutter power, \(n\) is the noise power, and \(L\) is the system and environment loss factor.

Too many parameters will increase the complexity of the algorithm. Here, let the radar main lobe performance constant be \(K\). In order to meet the requirements of fire control, the frequency of airborne radar is in a fixed X-band. The gain and loss difference between different radars can be ignored. So, these parameters can be set to constant, so we have

\[
K = \frac{G_{\text{SL}}^2 \lambda^2}{(4\pi)^3 L}.
\]  

(10)

The radar power can be obtained by electronic reconnaissance intelligence [26]. We assume the target radar to work in the optimal state, and the radar power can take the maximum value. It is necessary to filter the clutter reflected from the ground when radar looks down. The closer to the ground, the stronger the clutter power. When the radar looks sideways, the target falls into the main lobe clutter suppression area, so it cannot be detected [27]. The error brought by electronic reconnaissance intelligence can be offset to a certain extent by setting redundancy parameter. The more accurate the reconnaissance information is, the closer its value is to 1. Here, the radar range computing formula is updated from (9) to formula (11).

\[
R_{\text{max}} = \alpha \left( K \frac{P_{\text{av}} \cdot \text{RCS}}{n} \right)^{1/4}, \quad P_{\text{down}} = \alpha \left( K \frac{P_{\text{av}} \cdot \text{RCS}}{c + n} \right)^{1/4}.
\]  

(11)
Comparing the relative distance $D$ with the radar action distance $R$, when $R$ is greater than $D$, it indicates that the target has entered the radar detection area. The radar warning system determines whether the target’s radar is on or off. Only when the target radar shuts down and $R$ is greater than $D$, it is recognized as a silent penetration state.

### 4.3. Attack Tendentiousness Feature Extraction Based on Threat Assessment

With the development of radar technology, multiple adversaries may attack several targets at the same time to complete the complex cooperative attack task, so it is very important to determine the adversary’s attack tendency. In this section, a feature extraction method of enemy attack tendency based on threat assessment is studied to solve this problem, which can reduce the misclassification of tactical intention and improve the refinement of the recognition results. More importantly, this feature can improve the survival rate of our fighters and makes it possible to recognize the complex cooperative tactical intention.

Threat assessment is a comprehensive assessment result of target air-combat capability and space occupation [28]. There are seven indexes of fighter’s air-combat capability, covering firepower, maneuver, and thrust. Air-combat capability can be expressed as follows:

$$ T_C = \left[ \ln \left( \frac{V}{10 + 1} \right) + \ln \left( \frac{S + 1}{C_{16}/C_{17}} \right) + \ln \left( R + 1 \right) \right] v \cdot \text{NOR} \cdot r \cdot \text{ECM}, $$

where $V$ is voyage (km), $S$ is effective range of missile (km), $R$ is radar range (km), $v$ is velocity (mach), NOR is allowable normal overload (g), $r$ is push-weight ratio, and ECM is electronic countermeasure capability.

The target’s threat assessment value $T$ is obtained by weighting algorithm after normalization of $T_C$ and space occupancy information [28], which is not detailed in this paper. After the threat assessment values for all enemy targets have been calculated, it is common to deduce which target is more aggressive based on the order of the assessment values. A larger value means that the enemy has better space and more powerful weapons, so the probability of this enemy shooting down our side is higher.

Using the threat assessment values, we propose a new ranking method as shown in Figure 6. The traditional threat level does not represent the attack tendency of the target, and the targets with either a high or low threat may be attacked. In fact, the enemy is more likely to attack targets that are easier to destroy. In contrast to the traditional way to obtain the threat assessment values of all enemy targets to me, the attack tendentiousness feature extraction is to acquire the threat assessment results of the enemy to all our fighters. The higher evaluation value also represents a greater probability of shooting down. The enemy will be more inclined to attack the target with high assessment value. This feature is quantified as $F$ when the enemy tends to attack my friend and $M$ when the enemy tends to attack me.
5. Cooperative Tactical Intention Classifier Based on Entropy

The information of modern air combat is complex, variable, and incomplete. Therefore, to meet the performance requirements, this paper uses the C4.5 decision tree to realize the recognition of tactical intent. The decision tree has strong interpretability, which is also of great significance for military applications. C4.5 can tolerate missing data to cope with incomplete information [23] and can reduce model complexity by pruning. The definition of labels used by the cooperative tactical intent classifier is shown in Table 2.

There are 12 kinds of tactical intention output from the decision tree, which are divided into three categories: general tactical intention, general cooperative tactical intention, and complex cooperative tactical intention. The general tactical intent can be identified by existing methods. The difficulty of the above three kinds of tactical intention recognition increases in turn.

If a target shows relatively low aggressiveness, he may be on patrol or running away. Similarly, if the aggressiveness of a target is obvious, he may adopt corresponding tactics to attack according to different situations. This usually depends on the role of the target in the cooperative attack. The decision tree is a supervised learning method based on entropy, which hopes to achieve the fastest decline of entropy to acquire the most accurate segmentation of tags. Entropy represents the purity of samples. In sample set $N$, the probability of the $k$-th label is $p_k$. We have

$$\text{Ent}(N) = -\sum_{k=1}^{12} p_k \log_2 p_k,$$

$$N = \{EC, S, RP, DA, LO, RT, SP, DVA, L, CA, BS, F\}.$$

(13)

The features entered into the decision tree are shown in Tables 3 and 4.

In Table 4, the first feature is the recognized general tactical intentions, and the last three features come from feature extraction.

Information gain can be calculated according to information entropy. The information gain has a preference for features with a large number of classifications, where the intrinsic value is introduced to adjust the bias. The ratio of information gain to intrinsic value is called information gain rate, which is the criterion of the C4.5 decision tree. The larger information gain rate is better for classification. When missing values exist, the missing features set weights
according to the information gain rate and then carry weights to the next layer of nodes. At the leaf node, the label with the largest weight is selected as the output. The information gain rate of a feature can be defined as Formula (14), where is the feature set.

\[
\text{Gain}_{\text{ratio}}(N, a) = \frac{\text{Gain}(N, a)}{IV(a)} = \frac{\text{Ent}(N) - \sum_{i=1}^{t} \left( |N_i|/|N| \right) \text{Ent}(N_i)}{-\sum_{i=1}^{t} \left( |N_i|/|N| \right) \log_2 \left( |N_i|/|N| \right)},
\]

\[a = \{ \text{GT}, \text{MO}, \text{PI}, \text{TA} \}.\] \hspace{1cm} (14)

The training process for decision trees can be found in the fourth paragraph of the paper [4], which is not detailed here. After the test set has generated all the samples, the pruning operation is taken for the decision tree. If pruning does improve model performance, it is necessary, but if it affects model performance, the complexity and performance of the model need to be weighed appropriately.

It should be emphasized that the most important thing for the classification algorithm is the rationality of the label design. Some scholars only focused on the study of machine learning methods but ignored the acquisition of air-combat expert knowledge. Some unreasonable labels had been designed. For example, fighters do not have defense and protection tactics in the war zone, which are usually accomplished by special aircraft or ground air-defense circles. The labels designed in this paper take full account of the expert experience, so they are named reasonably and easy to understand.

Figure 15: Feature extraction of enemy attack tendentiousness. The horizontal coordinate is the time axis. The line chart at the top of the picture shows the results of two aircraft’s threat assessment to red3. The stacked histogram in the lower part of the image represents the extracted attack tendency features.

Table 6: Features and labels of some samples.

| Number | AI | ECM | Features | SS | MO | PI | TA | Label |
|--------|----|-----|----------|----|----|----|----|-------|
| 1      | y  | y   | Track    | *  | a  | n  | *  | EC    |
| 2      | y  | n   | Track    | y  | hp | n  | F  | BS    |
| 3      | y  | n   | Track    | n  | g  | n  | *  | CA    |
| 4      | n  | n   | Off      | y  | g  | n  | F  | S     |
| 5      | y  | n   | Track    | y  | g  | n  | F  | F     |
| 6      | y  | n   | Lock     | n  | g  | *  | M  | LO    |
| 7      | n  | n   | Off      | n  | g  | n  | M  | L     |
| 8      | n  | n   | Off      | n  | es | y  | F  | RT    |
| 9      | y  | n   | Track    | y  | a  | n  | M  | DA    |
| 10     | n  | n   | Track    | n  | g  | n  | F  | RP    |
6. Simulation Experiment and Discussion

This chapter validates the recognition effect of cooperative tactical intent through simulation experiments, which use more than 5000 samples as data set. The trajectory of the air-combat simulation experiment is shown in Figure 7. During the simulation run time, both sides will execute the cooperative air-combat task. The total running time of the simulation is about 50 s, and the flight path is drawn after the simulation is finished. The six fighters in the simulation are controlled by flight control software or a joystick. The red side is the enemy, and the blue side is us. In the experiment, we represented the changing process of the output results in a time-axis manner and explored the usefulness of this study through experimental analysis.

In the last part of the experiment, the recognition rate of different target tactical intention tags is verified based on the total samples. The total samples are generated from the simulation results of a different number of fighters. We will compare it with the research results of other scholars. The computer processor is Intel Core i7-8700 @4.60 GHz, and the system is 64 bit.

6.1. Introduction to Experimental Environment. This study relies on Shenyang Aerospace University and Liaoning Province Key Laboratory of Advanced Flight Control and Simulation Technology, and the research direction is the intelligent warfare method of UAV. To meet military requirements, methods with explanatory characteristics and low time complexity are often combined to achieve the performance of some more advanced methods. The main purpose of this study is to show that some easy-to-understand methods can also obtain good performance through ingenious design, which is not simply to stack the algorithm. Some of the experimental devices used in this paper are shown in Figure 8.

6.2. Experiments on Attack Intent Prediction Model. The models generated by different inner product functions are distinct, and we chose Gaussian kernel as the inner product function. The model has two adjustable parameters, penalty parameter $C$ and kernel parameter $\gamma$. There are significant differences in model performance when different parameters are used. $C$ represents the tolerance of misclassified samples, and $\gamma$ represents the scope of the kernel function. The performance of the model is determined by the training samples, but the training samples cannot be used as the criteria for evaluating the performance of the model. In this experiment, a different number of samples were randomly extracted as a training set, the rest as a test set. On this basis, the generalization performance of the model was validated by cross-validation, and the experimental results are shown in Figure 9.

The analysis shows that the accuracy of the model increases gradually as the number of training samples increases. When the number of samples is about 2000, the fitting of the model is completed, with a peak accuracy of 98.261%. Because of the cross-test method used in the experiment, the model has good performance in the face of different samples. The precision, recall, and $F1$ values are very close to the accuracy, so the specificity and sensitivity of the classification are reliable. SVM effectively reduces the dimension of low correlation parameters. The fitting speed of the model is very fast, and it can cope with the situation that training samples may be insufficient in wartime.

In the simulation experiment in Figure 7, the attack intentions of four targets against blue2 during the simulation run-time are shown in Figure 10. In the beginning, red 1 is close to blue2, and then red 1 goes around to the rear of blue2 to attack. Red2 and red 3 turn around after a short advance. Because red4 is always far away from blue2, it does not show any attack intention. The above analysis shows that the results of the model are consistent with the actual situation.

6.3. Experiments of Collaborative Tactical Feature Extraction

(1) Mobile occupancy feature extraction

The maneuvering occupancy features of the red four fighters were extracted using the method in Section 4.1, and the experimental results are analyzed using red 4 as an example. Eight primary features were used as network inputs, and the trends of AV, VV, ARV, CAV, and NO vs. time are shown in Figure 11. AS, D, and AAV did not change in the experiments, and their feature values were fast, near, and undiminished, respectively. This section of the experiment took 10 s as the starting point, every 50 ms as a cycle, and each cycle refreshed the data.

The recognition probability of mobile occupancy of the root node is shown in Figure 12, and the output result is the one with the highest recognition probability. In the
figure, the coordinate axis of the sampling period is zoomed according to the scale, and "10 s, 1c" represents the first cycle of the 10th s. Analysis of Figure 11 shows that the output will change with the input feature value change and will converge in several cycles. The outputs are correctly identified as high-performance occupancy in the fifth cycle of the 10th s, general occupancy in the fourth cycle of the 20th s, and aggressive occupancy in the second cycle of the 28th s, respectively. Experiment results show that the method is real-time and effective.

(2) Silent penetration feature extraction

In order to verify the accuracy of radar model, we present the result of a full angle RCS simulation of blue1 in Figure 13.

When the airborne radar looks up, it intercepts the target from the time domain and is not affected by clutter, so has a long detection range. Radar intercepts target from the frequency domain when looking down, and the lower the altitude, the more obvious the effect of ground clutter on the detection distance. In addition, when the radar wave is nearly perpendicular to the target, the echo is in the main lobe clutter suppression area in the frequency domain, and the radar range is almost zero. We took red3 as the research object. Here, it was assumed that the average transmitting power of a certain radar equipped with red3 was 1000 W, the main lobe gain was 33.5 dB, and the operating frequency was 10 GHz. The simulation of the radar detecting range is shown in Figure 14, whose curve has a good fit with the RCS curve, which can correctly reflect the change of radar detection range when looking up and down. The above experiments verify the accuracy of the radar model.

Based on the accuracy of the model, the effectiveness of the silent penetration feature extraction method is verified by simulation experiments. Table 5 shows the silent penetration feature extraction results of blue1 on red3. In the experiment, some data changed at 0 s, 16 s, 20 s, and 32 s. At 16 s, blue1 entered the detection area of red3, and red3 turned off the radar and improves the speed. The result of feature extraction was yes. At 20 s, the radar of red3 was turned on and the feature extraction result was no. At 32 s, red3 flew out of the radar detection area, and the feature extraction was yes. Simulation results show that the feature extraction results are consistent with the actual situation.

The first column of the table is time. The second column is the comparison result between the radar detection range $R$ and the actual range $D$ with the larger one being reserved. The third column indicates whether the radar is on or off. The last column is the result of feature extraction.

(3) Attack tendentiousness feature extraction

The experiment inferred which target red3 tended to attack by analyzing the threat assessment results of blue1 and blue2 to red3. The highest value of threat assessment is 10. The higher the score, the higher the threat. In this section, if red3 tends to attack the fighter on the blue side, the result of feature extraction is $M$; otherwise, the recognition result is $F$. 

![Figure 17: General tactical intention recognition results.](image1)

![Figure 18: An example of decision tree for cooperative tactical intention recognition.](image2)
Figure 15 records the threat assessment values and feature extraction results for the first 40 seconds. In the initial stage of simulation, red3 took blue1 as the target. Halfway through, red3 gave up attacking blue1 and turned to approach blue2. Then, red3 stopped attacking and kept a safe distance from us while keeping his back to us. This tactical intention is often called lure. The change of threat assessment value in the graph corresponds to the change of attack tendentiousness.

6.4. Experiments on Target Tactical Intention Recognition. The above experiments have established the advanced features of the seven dimensions. Next, 300 typical samples were selected from the sample library for decision tree training. These samples were randomly selected to ensure that all category labels are covered. We deleted some of the features from some samples to observe the tolerance of the method to missing values. Because the number of samples in this experiment is small, it can verify the small sample performance of the algorithm at the same time. Features and labels of some samples are shown in Table 6.

Ten of the samples are selected in the table with the missing feature being indicated by *. In the values of the feature RS, track and lock mean the radar is on.

The intention recognition of cooperative tactics is divided into two steps. The first step is the general tactical intention recognition based on the high correlation feature, which is presented by 6.3.1. The second step is cooperative tactical intention recognition based on cooperative tactical features and general tactical intention identified in the first step, which is presented in 6.3.2.

(1) General tactical intention recognition

The label set for general tactics is defined as GT = {EC, S, RP, DA, LO, RT}, and the feature set is defined as $a = \{AI, ECM, RS, SS\}$. The decision tree generated by the training in this experiment is shown in Figure 16, which has a complete structure and can still effectively distinguish six general tactical labels with missing values.

Figure 16 shows that the decision tree generated by the training is shown in Figure 16, which has a complete structure and can still effectively distinguish six general tactical labels with missing values.

General tactical intention identification results are shown in Figure 17. We still use the time axis to reflect the label changes. Five general tactical intentions emerged during the 50 seconds of the simulation process. Each fighter on the blue side recognized the tactical intention of the four targets on the red side, and each target’s intentions were correctly identified.

(2) Cooperative tactical intention recognition

Using the identified general tactical intention results as the input features, a more complex classification of cooperative tactical intention is performed. The features and labels of cooperative tactic intention are described in chapter 4. The decision tree generated by the training is shown in Figure 18, which has undergone mild pruning and can effectively distinguish 12 cooperative tactical labels. Although the number of samples is insufficient, it still finishes the task well in the simulation experiment. This means that the method can also tolerate the special case of insufficient samples to some extent in identifying the opponent’s cooperative tactical intention.

In the process of confrontation, the intention recognition results of four red fighters and two blue fighters are shown in Figure 19. Each plane had a different task. Red1 chose to turn away from the battlefield first, then turned around and attacked suddenly. Red2 was a fighter with active electronic countermeasure equipment. Red3 turned into a lure after the encounter with the enemy. Red4 chose to increase energy first and then went around to the rear of the target to launch an attack. The experimental results are consistent with the actual situation.

6.5. Contrast Experiment and Discussion. To verify the tactical intention recognition rate of this method, we used 3000 sample data to conduct a comparison experiment. Because the presupposition of the comparative experiment should be consistent, we deleted samples with missing values and do not perform precision-losing pruning on the decision tree. This experiment was compared with the following research: LSTM neural network combined with a decision
Among them, the paper [3, 29] thinks that it can recognize both CT and GCT tags at the same time. As shown in Figure 20, the recognition rates of GT, GCT, and CCT by the method presented by this paper are 98.93%, 98.09%, and 92.22%, respectively. Therefore, compared with the traditional methods, the methods proposed in this paper can improve the recognition rate of all kinds of tactical intentions to a certain extent. The recognition rate of GT is slightly higher than that of literature [3, 4], significantly higher than that of literature [29]; the recognition rate of GCT is significantly higher than that of literature [3, 29] whose algorithm has a poor recognition rate for this kind of tactics. The method of this paper can accomplish the CCT recognition task to a certain extent, which reflects the innovation of this article, and there is still room for improvement of the recognition rate. The average running speed of this method was detected after model generation. For the stability of the program, a cycle is set to 50 ms. Considering that the DBN model requires a maximum of five cycles to complete convergence, this method can identify the target’s tactical intent within 250 ms. Experiments show that the results of this study propose a promising way for target tactical intention recognition in multi-aircraft cooperative air combat.

7. Conclusion

This paper makes in-depth research and analysis on target tactical intention recognition in multi-aircraft cooperative air combat. The validity of the method is verified by simulation and comparison experiments.

(1) In this paper, we first propose the multi-aircraft cooperative tactical intention recognition method. The recognition rates of general tactics, general cooperative tactics, and complex cooperative tactics are 99.13%, 98.09%, and 92.22%, respectively, when the sample library is sufficient. The overall recognition ability is better than the traditional research results, and the small sample performance is better, which reflects the advancement of this method.

(2) Based on the parameters obtained online on the battlefield, the methods can deal with issues with vaster and more dynamic state space, which has good application prospects in collaborative air combat, simulation training, and so on. This method works with incomplete and uncertain information, avoid the interruption of algorithm operation, and has good robustness.

(3) The algorithm complexity of the tactical intention recognition method proposed in this paper is relatively low, and all nodes are pretrained or set up to avoid the repeated reasoning process in the running process. The recognition model has a clear structure and strong interpretability. The single operation speed reaches millisecond level, which meets the real-time requirements for application.

Data Availability

The [DATA TYPE] data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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