Air-to-Air Combat Tactical Decision Method based on SIRMs Fuzzy Logic and Improved Genetic Algorithm

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Abstract. Multiple UCAVs air-to-air combat poses great challenges such as a vast number of input variables, complex confrontation rules that are difficult to be obtained, etc. A tactical decision method based on single input rule modules (SIRMs) dynamically connected fuzzy inference model and an improved adaptive genetic algorithm (IAGA) for multiple UCAVs air-to-air combat is proposed in this paper. Considering the "dimension disaster" problem in traditional fuzzy rules design due to increasing input variables, SIRMs dynamically connected fuzzy inference model is used to make tactical decision, where all input variables are decoupled by SIRMs and the number of rules is greatly reduced. The model output is merged by adding the results of all decoupled rules with dynamic importance degrees. As accurate confrontation rules are difficult to be obtained in practice, the IAGA is designed to optimize the consequent part of the rules, which can produce detailed rules using only a simple rule skeleton. Two representative 2 vs 1 cases are simulated. The results show the validity, universality, and expansibility of the tactical decision method proposed in this paper. It also can be easily extended to *n* vs *n* cases in different combat situations.

Keywords: Multiple UCAVs, Air-to-air combat, Tactical decision, SIRMs, Adaptive genetic algorithm

1 Introduction

Unmanned combat aerial vehicles (UCAVs) are increasingly applied to the modern air combat [1], of which the mission features multi-targets and multi-tasks, thus is often difficult to be accomplished by single UCAV [2]. In this situation, multiple UCAVs system shows obvious advantages. However, UCAVs of multiple UCAVs system struggles to make reasonable immediate tactics decision autonomously in unexpected situations even if those are controlled by a pilot. Therefore, an efficient and reliable tactical decision algorithm for multiple UCAVs system is required.

To address this tactical decision problem for multiple UCAV system, five methods were primarily used in the literature, based on theories of matrix game, influence diagram, differential game, expert system, and rule inference, respectively. For instance, a game-matrix approach was used to make decision for low-flying aircraft during one-on-one air combat over hilly terrain, and the decisions were made by comparing scores based on the predicted orientation, range, velocity, and terrain clearance for various maneuver combinations of both aircraft in [3]. Influence diagrams method was employed to establish a continuous decision-making process of cooperative multi-UAVs air combat in [4-6]. In [7-8], problem of optimal maneuver decision on two-vs-one combat cases was researched based on differential game theory. The building of a decision support mechanism based on expert system for multiple air combat tactical maneuvering was discussed in [9]. An air-to-air combat simulation method based on rules was proposed in [10-12], of which the decision-making results obtained by this method were close to the actual flight actions of pilots. In addition, a tactics algorithm dividing the combat into several group-to-group combats was proposed in [13].

However, the above tactical decision methods generally have the following problems: with the increase of aircraft sorties, the “dimension disaster” of corresponding problem formulation (the matrix dimension in matrix game, the rule number in rule based methods, etc.) may appear. Moreover, for the widely applied rule inference methods, detailed expert rule library is difficult to construct due to lack of data. For solving above problems, in this paper a tactical decision method based on single input rule modules (SIRMs) dynamically connected fuzzy inference model [14-15] and improved adaptive genetic algorithm (IAGA) for multiple UCAVs air-to-air combat is proposed. The “dimension disaster” problem can be solved by using SIRMs dynamically connected fuzzy inference model. In this model, a SIRM is designed for each input variable, which decouples all input variables thus the number of rules is greatly reduced. The model decision output is obtained by adding the results of all decoupled SIRMs with dynamic importance degrees (DIDs). As accurate confrontation expert rules are difficult to be obtained in practice, the IAGA is designed to optimize the consequent parts of the rules. In IAGA, elitist retention strategy is used for selection which can accelerate population evolution. A dynamic crossover probability function is designed for crossover which can relieve the “precocity” of population [16]. The idea of simulated annealing (SA) [17] is used for mutation which can increase the climbing ability of GA. Then detailed rules for every decision cycle in different situations can be produced by IAGA with a simple rule skeleton.

2 Preliminary of SIRMs dynamically connected fuzzy inference model

In the traditional fuzzy inference model, all input variables are coupled and regarded as antecedent variables of fuzzy rules. Therefore, it brings the problem of “dimension disaster”. In the SIRMs dynamically connected fuzzy inference model, all input variables are decoupled by SIRMs. For a system with N inputs and M outputs, it can be divided into M N-input-1-output subsystems. Moreover, all input variables are coupled again by DID. The role of each input variables can be strengthened or weakened for output by changing DID.

For each N-input-1-output system, the SIRMs dynamically connected fuzzy inference model includes just N modules as:

$$SIRM\ i: \{R_j^i: if \quad x_i = A_j^i\ then \quad \Delta u_i = C_j^i\}_{j=1}^{h_i} \tag{1}$$

Here, $SIRM\ i$ is the SIRM of the i-th input. R_j^i stands for the j-th rule. x_i is the input, and it is the sole antecedent variable. Δu_i is the output of $SIRM\ i$, and it is the consequent variable. A_j^i and C_j^i are separately the membership function of the antecedent variable x_i and the consequent variable Δu_i. Here, $i = 1, 2, ..., n$, $j = 1, 2, ..., h_i$ with h_i as the rule number of the i-th input.

The inference result Δu_i can be obtained by any given defuzzification method such as product-sum-gravity method and simplified inference method [17]. In this paper, min-max-inference engine, single point fuzzification, and centroid defuzzification are used to gain Δu_i .If the value of the variable x_i ($i = 1, 2, ..., n$) is given as x_i^0, the agreement of the antecedent part of j-th rule of $SIRM\ i$ simply becomes h_j^i. Supposing the output universe of discourse is Δu, the inference result Δu_i^0 of $SIRM\ i$ can be gain by

$$h_j^i = A_j^i(x_i^0) \tag{2}$$

$$\Delta u_i^0 = \sum_{j=1}^{m_i} h_k^i C_k^i \Big/ \sum_{j=1}^{m_i} h_k^i \tag{3}$$

To address the problem that each input x_i has different influence for Δu, a DID w_i^D is defined by the SIRMs dynamically connected fuzzy inference model as:

$$w_i^D = w_i^0 + B_i \Delta w_i^0 \tag{4}$$

Here, w_i^0 and B_i are two tunable parameters. In this paper, we trivally set $w_i^0 = 0, B_i = 1$, leaving Δw_i^0 as the only dynamic variable related to x_i. Similarly to the process of calculating Δu_i^0, we can construct additional SIRMs and finally obtain Δw_i^0. Details are omitted for page limitation.

The output of SIRMs dynamically connected fuzzy inference model Δu^0 can then be obtained by integrating Δu_i^0 and Δw_i^0. Suppose each input is linearly related to the DID, then we have

$$\Delta u^0 = \sum_{i=1}^{n} w_i^D \cdot \Delta u_i^0 \tag{5}$$

3 UCAVs air-to-air combat tactical decision design

In this section, a tactical decision method based on the aforementioned SIRMs dynamically connected fuzzy inference model and an IAGA for multiple UCAVs air-to-air combat is proposed. In this method, the number of rules for fuzzy inference increases linearly rather than exponentially with the number of UCAV. The overall structure diagram is given as Fig. 1.

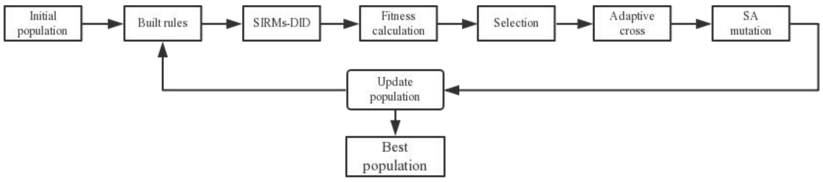


Fig. 1. The structure diagram

3.1 Design of tactical decision method based on SIRMs dynamically connected fuzzy inference model

The core logic of air-to-air combat is to gain good air occupation. The number of input decision variable is 3 and the input decision variable are chosen as the relative distance of the two sides D, the angle of entry α, and the azimuth β, respectively. The number of output variable is 2 and the output variables are variation of altitude Δh and flight path azimuth $\Delta\varphi$. In multiple UCAVs air-to-air combat, decision for each single aircraft is affected by other aircraft in the environment. Hence, following the SIRMs fuzzy inference model in section 2, the decision-making aircraft has $6(m+n-1)$ input variables in the m vs n confrontation and the structural chart of each decoupled SIRM of input variable is designed as Fig. 2. It can be seen that the design of each decision variable and the decision system for each UCAV is independent. This kind of distributed design can greatly improve the expansibility and tailorability of multiple UCAVs combat system.

The fuzzy set of all variables is defined as Table 1. The corresponding membership functions for D, α, β, Δh and $\Delta\varphi$ are triangular, and those for N, ZO, and P of Δw_i^0 are Gaussian. It can be calculated that for the confrontation of m vs n, conventional fuzzy model needs $350^{(m+n-1)}$ rules while the SIRMs dynamically connected fuzzy inference model needs only $68(m+n-1)$ rules. The outputs are obtained following the SIRMs dynamically connected fuzzy inference model given in section 2. The rules of each fuzzy inference are obtained by IAGA.

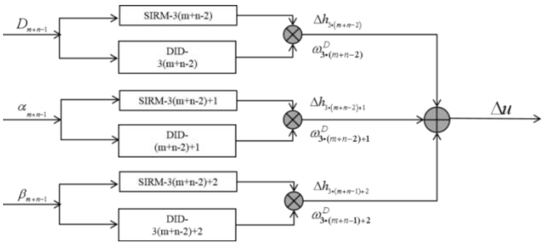


Fig. 2. Structural chart of each decoupled SIRM of input variable

Table 1. The fuzzy set of input and output variables.

Variable	The fuzzy set					
D	NB	NS	ZO	PS	PB	
α	NB	NS	ZO	PS	PB	
β	NB	NM	NS	ZO	PS	PM	PB
Δh	NB	NM	NS	ZO	PS	PM	PB
$\Delta\varphi$	NB	NS	ZO	PS	PB		
Δw^D	N	ZO	P				

3.2 IAGA for multiple UCAVs air-to-air combat

Since accurate confrontation rules are difficult to be obtained in practice, here IAGA is designed to optimize the consequent parts of the rules to get the complete rules. The consequent parts of all rules form an individual and 50 individuals form a population in this paper. Each gene on the chromosome of individual corresponds to a fuzzy set of output variables. Moreover, symbolic encoding is used in this paper. Each fuzzy set is labeled as a sequence number. For example, the fuzzy set N, ZO, P of Δw^D correspond to 1,2,3 respectively. The overall gene number of chromosome is $68(m+n-1)$.

Fitness calculation

The fitness calculation of a decision-making UCAV can be divided into three cases. If any UCAV of decision-making side is shot down, the fitness value $f=-100$. If there is a stalemate, the fitness is related to real-time combat situation and the range is: [0-60]. If there is a winning, the range of fitness value is: [60-100]. The fitness is calculated as:

$$f=\begin{cases} -100 & \text{Be shot down} \\ 60\sum_{i}^{m+n-1} T_{avg}(i)/(m+n-1) & \text{Stalemate} \\ 40\left(\sum_{i}^{m+n-1} T_{\max}(i)\right)^{r(1)}\left(1-\dfrac{s-1}{100}\right)^{r(2)}+60 & \text{Winning} \end{cases} \tag{6}$$

Here, $T_{avg}(i)$ is the average of situation assessment value after completing each decision actions of i-th UCAV in a combat. The situation assessment value is obtained according to the relative position relationship between the two sides. Details can be found in our previous work [18]. $T_{\max}(i)$ is the maximum value of situation assessment value after each completed decision actions of i-th UCAV in a combat.

Section

The elitist retention strategy is adopted. It copies the s individuals (s = 5) with higher scores in the parent generation to the next generation, and then takes the binary tournament selection to select the remaining individuals.

Adaptive Crossover

Each gene position represents the value of different output fuzzy sets, so it is necessary to ensure that the sequence of gene segments on each chromosome remains the same after crossover. Moreover, **a** dynamic crossover probability function is designed in this paper. It has three aims: relieving the "precocity" of population, improving the global optimization performance, and making individuals maintain certain cross probability under a high fitness value [19].

$$pc=\begin{cases} pc_2+\dfrac{pc_1-pc_2}{1+\exp(A(1-\dfrac{2(f_{avg}-f^{'})}{f_{avg}-f_{\min}}))} & f_{\min}\le f^{'}\le \dfrac{f_{\min}+f_{avg}}{2} \\ pc_2+\dfrac{pc_1-pc_2}{1+\exp(A(1-\dfrac{f^{'}-(f_{avg}-f^{'})/2}{(f_{avg}-f^{'})(f^{'}-f_{\min})}))} & \dfrac{f_{\min}+f_{avg}}{2}<f^{'}\le f_{avg} \\ pc_3+\dfrac{pc_2-pc_3}{1+\exp(A(\dfrac{2(f^{'}-f_{avg})}{f_{\max}-f_{avg}}-1))} & f_{avg}<f^{'}\le f_{\max} \end{cases} \tag{7}$$

Here, $pc_1=0.9, pc_2=0.6, pc_3=0.3, A=9.9034$, f_{avg}, $f_{\max}$, and $f_{\min}$ is the average, maximum, and minimum fitness of the population. $f^{'}$ is the larger fitness of the two crossing individuals.

The benefits of the dynamic crossover probability function lie in the following three aspects:

(1) Smoothing the probability curve near f_{avg} to ensure that there is a larger probability value;

(2) Ensuring that the better individuals have certain probability values;

(3) Pulling down the probability value near $f_{\max}$ to preserve as many good individuals as possible.

SA mutation

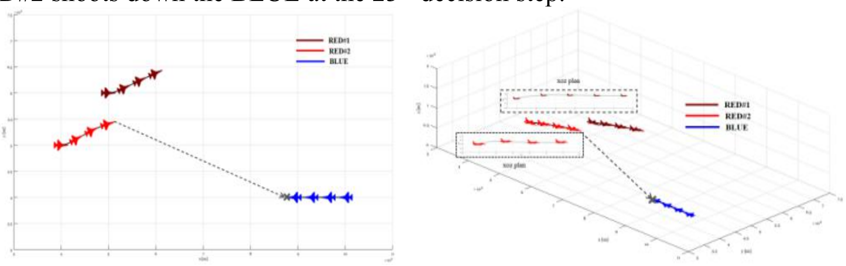
Mutation occurs with a certain probability. If there is mutation, the difference between the new fitness after variation and the fitness before variation is calculated. If the fitness after variation is larger, the variation is accepted. If the fitness after variation is smaller, the variation is determined by a certain annealing probability $\exp(\delta/T)$. Here, δ is the difference between the fitness value before mutation and the fitness value after mutation. T is a value that decreases with time. This mutation contains the idea of simulated annealing (SA) [20] and increases the climbing ability of GA.

4 Simulation

Two simulation cases are carried out in this part. Both case 1 and 2 are based on the background of 2 vs 1 confrontation. The method also can be easily applied to *n* vs *n* multiple UCAVs air-to-air combat.

4.1 Case 1

In this case, the RED adopts the tactical decision method proposed in this paper, and the BLUE is taking simple linear maneuver. Fig. 3 (a) shows that the two REDs constantly change their flight path azimuth to find the best angles to attack the BLUE. The algorithm ensures that they have a large angle of entry to the blue side, which is not conducive to the BLUE attack. In Fig. 3 (b), it can be seen that the two red UCAVs are also constantly raising the altitude to obtain a higher energy advantage. With the change of flight path azimuth and the expansion of energy advantage, RED#2 shoots down the BLUE at the 23rd decision step.



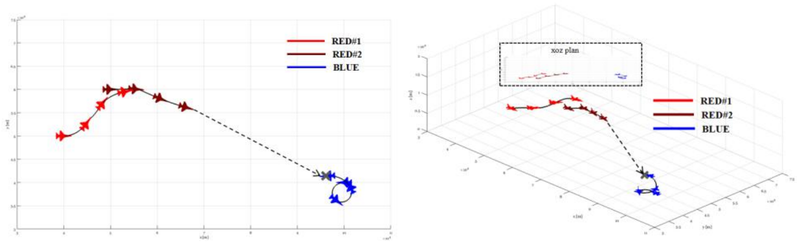
(a) *xoy* Plane (b) *xyz* Plane

Fig.3. 2 (tactical decision method proposed in this paper) vs 1 (linear maneuver)

4.2 Case 2

In order to further verify general adaptability of the method, maneuver strategy of the BLUE is set as the optimized strategy by RED#1 in case 1. As can be seen from Fig. 4, the focus of the REDs is the same as the above experiment. In addition, compared with RED#2, RED#1 is under a bad initial condition, then its flight path azimuth angle is changed continuously by the guidance of RED#2. RED#1 forms a following and shielding tactic with RED#2. When the simulation step is 34, the BLUE is shot down successfully.

Table 2 is the data of the results of IAGA for case 1 and case 2. In Table 2, it can be seen that the method can greatly improve the quality of the individuals in the population. The method is suitable for more complicated confrontations.



(a) *xoy* Plane (b) *xyz* Plane

Fig.4. 2 (tactical decision method proposed in this paper) vs 1 (smart maneuver)

Table 2. The data of the results of IAGA for case 1 and case 2

Case 1					
Initial winner number	Last winner number	Improvement	Initial fitness	Last fitness	Improvement
35	47	24%	86.7113	88.0129	1.3016
Case 2					
Initial winner number	Last winner number	Improvement	Initial fitness	Last fitness	Improvement
0	46	92%	18.8158	91.3820	72.5662

5 Conclusions

In this paper, a tactical decision method based on SIRMs dynamically connected fuzzy inference model and an IAGA for multiple UCAVs air-to-air combat is proposed. the “dimension disaster” of fuzzy rules caused by large number of input variables is solved by SIRMs. The problem of accurate rule construction of fuzzy inference is solved by IAGA. The experiment proves the validity, universality and expansibility of this method. Moreover, the method also can be easily extended to *n* vs *n* cases in different combat situations.

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