Knowledge Acquisition for the Air Combat Based on GWO

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Abstract. The problem of knowledge acquisition for the air combat of fighter is studied, and a way to acquire knowledge from massive flight parameters data is put forward. First, expert system of air combat is built; then for flight maneuver knowledge extraction, a method based on grey wolf optimization (GWO) is proposed, in order to obtain simple and effective knowledge, and design a new evaluation function of the GWO algorithm. Finally, the simulation results of horizontal right turn and single plane loop verify that the knowledge extraction method of flight maneuver is effective and feasible.

1. Introduction
Unmanned Combat Air Vehicle (UCAV) can independently perform combat missions in air battlefield. Any equipment or person beside UCAV will not participate in the whole Combat process, during which UCAV autonomously performs a series of processes from situational awareness to trajectory planning. To research UCAV autonomous air combat better, the air combat knowledge base must be possessed firstly. How to acquire air combat knowledge quickly, economically and safely is a difficult problem in constructing UCAV combat knowledge base and one of the key technologies of UCAV autonomous air combat.

Knowledge acquisition refers to the process of transforming knowledge from external knowledge source into a form that can be recognized by the computer through some methods [1]. Knowledge acquisition methods mainly include concept lattice [2], rough set [3], machine learning [4] and statistical learning [5]. At present, the research closely related to air combat knowledge acquisition mainly focuses on the flight action recognition in the analysis of flight accidents. Literature [6] proposes a flight motion recognition method based on genetic algorithm, which takes flight data as the research object and applies the improved genetic algorithm to obtain the flight motion digital features for recognition. Aimed at the relatively difficult problem of building knowledge base of expert system, rough set theory proposed in literature [7] is adopted to extract features of flight data mode, and simulation results show that the extraction method was effective.

Over the years, air combat confrontation and flight training have accumulated a lot of data, which provides a large number of samples for UCAV to extract air combat knowledge through data processing. The research of existing air combat knowledge acquisition is not comprehensive. Hence, the paper designs flight action rules automatic extraction method based on Grey Wolf Optimization algorithm (GWO) [8], and the horizontal right turn and single plane loop are analysed.

The reminder of this paper is organized as follows: The air combat expert system knowledge base is presented in Section 2. The flight data characteristic is presented in Section 3. Flight action
knowledge acquisition method based on GWO algorithm is designed in Section 4. The experimental results on two maneuvers are analysed in Section 5. Finally, the conclusion is given in Section 6.

2. Air combat expert system knowledge base

Expert System (ES) that can imitate the behavior of experts is a computer program developed in 1965 by Stanford University. Through development and research of 50 years, Expert System has become a hot research issue in the field of artificial intelligence and has been widely used in various fields [9]. The expert system is generally composed of three parts: knowledge base, database and inference engine. Its structure is shown in figure 1. Knowledge base is the key to building expert system, but it is also the biggest "bottleneck" problem. The foundation of constructing expert knowledge base lies in the method of knowledge acquisition. UCAV expert system knowledge base is mainly based on pilot's experience knowledge, which can be acquired automatically.

![Figure 1. Expert System](image)

3. Flight data characteristic

The information recorded by the flight data recording system includes the engine system, flight control system, flight attitude, inertial system, throttle, atmospheric system and other parameters of the aircraft. Coupling relationship between some parameters makes data processing difficult, so the flight action rules are firstly extracted from complicated information to find out some related attributes of obvious flight movements by experts. Then the related attributes are extracted from the flight data. The flight action rule properties are obtained by statistical processing of initial scope.

The parameters closely related to flight action are: height, speed, course Angle, roll Angle, longitudinal overload, normal overload and so on. The data samples of these parameters in a certain period of time are counted, and the following results can be obtained: height increment, velocity increment and heading Angle increment at the beginning and end time; During the process, the accumulative increment of height, velocity, course Angle, roll Angle and pitch Angle are considered. Addition to above attribute parameters, the maximum and minimum roll Angle, maximum and minimum pitch Angle, maximum and minimum longitudinal overload, maximum and minimum normal overload and other attribute parameters should be included. According to the fine degree of extraction of flight action rules, some attributes can be selected from the above mentioned attribute parameters for combination. Generally speaking, the higher the degree of precision is required, the more attribute parameters are required.

To extract flight action rules, it is also necessary to number the above attribute parameters. In this paper, \( K_1, K_2, \cdots, K_n \) denotes the attribute parameters sequence, where \( K_q \) denotes the \( q \)th parameter in the rules, and \( h, v, \psi, \phi, \gamma, n_s, n_t, sta \) and \( end \) denote height, velocity, heading Angle, rolling Angle, pitching Angle, longitudinal overload, normal overload, initial moment and terminal moment, respectively. Parameter attribute values are calculated according to the following formula.

The formula for calculating the increment between the initial and terminal moment is given as follows:

\[
K_q = W_{end} - W_{sta}
\]

where \( q \) is the ordinal number of the parameter, \( W \) can express \( h, v \) and \( \psi \). When \( W \) denotes \( h \), the above equation is the height difference calculation formula.

Cumulative incremental calculation formula is presented as follows:

\[
\text{Cumulative Incremental Calculation Formula} = K_n = \sum_{q=1}^{n} K_q
\]
\[ K_q = \sum_{i=1}^{\text{end}} |W_{i+1} - W_i| \]  

(2)

where the subscript \( i \) represents the \( i \)th moment. As can be seen from the above equation, the calculation of cumulative increment is the sum of the absolute difference between the value of the last moment and the value of the previous moment.

The formulas for calculating the minimum and maximum limit values are given as follows:

\[
\begin{align*}
K_q &= \max \{W_{\text{sta}}, \ldots, W_{\text{end}}\} \\
K_q &= \min \{W_{\text{sta}}, \ldots, W_{\text{end}}\}
\end{align*}
\]  

(3)

According to the above formula, the limit value can be calculated as the maximum or minimum value of the data from the initial time to the end time of the parameter in the sample.

4. Flight action knowledge acquisition method based on GWO algorithm

4.1. Encoding method

Flight action rules are extracted from flight data samples. For a specific action, the corresponding positive example samples and negative example samples should be obtained. Through the positive example samples, the limit values of each parameter attribute can be obtained according to the above calculation equation (1), (2) and (3). According to the covering force of flight action rules on positive examples and the repulsive force of negative examples, the appropriate fitness function is defined. Through the optimization of grey wolf optimization algorithm, the final flight action rules can be obtained, where \( \{K_1 > \min(K_i) \& K_2 > \min(K_i) \& \cdots \& K_r < \max(K_i)\} \) is defined as knowledge rule. It can be seen that the flight action rules are the combination of parameter attributes.

Considering that the action rules are represented by selecting some flight parameter attributes for combination in this paper, it is most appropriate to encode the attribute selection with binary code. The code value 1 indicates that the attribute is selected, and 0 indicates that the attribute is not selected. The parameter attributes are coded and sorted by \( \{\min(K_1) \max(K_1) \ldots \min(K_n) \max(K_n)\} \). Through the optimization of the grey wolf optimization algorithm and the evaluation of the fitness evaluation function, the optimal grey wolf individual can be obtained, such as 001001000001, and the corresponding flight action rule is \( \{K_1 > \min(K_i) \& K_2 > \min(K_i) \& K_3 < \max(K_i)\} \), where \( \min(*) \) and \( \max(*) \) are the limit values of the related parameter attributes calculated according to the positive example sample statistics. The limit values are the constant values.

4.2. Position update strategy based on Grey Wolf optimization algorithm

Grey Wolf optimization algorithm is a new bionic swarm intelligence algorithm proposed by Seyedali, Seyed and Andrew in 2014. The algorithm has the characteristics that few parameters need be tuned. Each individual in the wolf pack is a potential solution, and the grey wolves at the highest three levels are the optimal solution including the optimal solution, excellent solution and the sub-optimal solution, respectively. The location of prey and the location of other grey wolves are determined by three excellent solutions. Because binary coding is adopted, the original grey wolf position is not suitable in this paper. The update strategy is redesigned as follows.

The distance between the grey wolf individual and the prey is:

\[ D = C \& X_p(t) \oplus X(t) \]  

(4)

\[ X(t+1) = X_p(t) \oplus A \& D \]  

(5)

\[ C = r_1 \]  

(6)

\[ A = a \& r_2 \oplus a \]  

(7)
where ⊕ means xor operation, & represents and operation, and \( r_1 \) and \( r_2 \) are random coding sequence with the same dimension as grey wolf individual, respectively. \( D \) is the distance between the prey and the grey wolf, \( t \) is the number of iterations, \( C \) and \( A \) are the coefficient vectors, \( X_\rho \) is prey position vector, \( X \) is grey wolf position vectors, and \( a \) are distance control parameter.

The mathematical model of tracking prey of wolves is described below:

\[
\begin{align*}
D_\alpha &= C_\alpha X_\alpha(t) \oplus X(t) \\
D_\beta &= C_\beta X_\beta(t) \oplus X(t) \\
D_\delta &= C_\delta X_\delta(t) \oplus X(t) \\
X_1 &= X_\alpha \oplus A_\alpha \& D_\alpha \\
X_2 &= X_\beta \oplus A_\beta \& D_\beta \\
X_3 &= X_\delta \oplus A_\delta \& D_\delta \\
X_\rho(t+1) &= X_1 \oplus X_2 \oplus X_3
\end{align*}
\]  

(8)

(9)

(10)

Where, equation (10) can judge the location relationship between grey wolf individual \( \omega \) and prey based on locations of \( \alpha, \beta, \delta \).

### 4.3. Fitness function design

It is very important to design a proper fitness evaluation function for extracting excellent flight action rules. The rules extracted by the algorithm should contain positive example samples and exclude negative example samples as much as possible, and the extracted rules should be concise with low redundancy. Therefore, the fitness function is designed as follows:

\[
f(a, b) = y_a \ast y_b
\]

(11)

\[
y_a = \lambda \frac{a}{F} + \frac{a}{a+1} \cdot \frac{D-b}{D+b}, \quad y_b = \sum_{i=1}^{b} \frac{1}{(b-i)^2 + 1}
\]

(12)

where \( F \) is the total number of negative examples. \( \lambda \) is the proportion coefficient which represents the proportion between the correctness and simplicity of the rule. Through the experiment comparison, \( \lambda = 4 \) is more ideal. \( a \) is the number of the current repulsive negative examples. \( D \) is the dimension of the solution. \( b \) is the number of attributes contained which is the number of 1 in coding. The change trend of fitness function is shown in figure 2. It can be seen that the value of \( y_b \) in the whole interval tends to smooth. The change on both ends of range is bigger, so the purpose of design is to ensure that the number of attributes is not too simple or too redundant. The sub-function \( y_a \) reflects the ability of excluding negative examples. As can be seen from the figure 2, when \( b \) is fixed, with \( a \) increasing, the value curve of \( y_a \) shifts up, and the function value increases. Hence, the fitness of function \( y \) shifts up. For any thick blue curve \( y \) in the figure 2, its value increases at the initial stage and then gradually decreases with the increasing of \( b \).

![Figure 2. The change trend of fitness function and sub-functions](image-url)
4.4. Flight action rule extraction process

Figure 3 shows the flight action rule knowledge extraction flow chart based on grey wolf optimization algorithm. Firstly, a certain flight action that requires knowledge extraction is determined. A proper number of positive data samples and negative data samples are selected from the flight history data. On this basis, the attribute characteristic quantity of flight parameters is obtained through statistical processing. Then, domain experts preliminarily screen out the attribute combination of key flight parameters that can represent the action. After the attribute combination is symbolized, grey wolf optimization algorithm is adopted to optimize, and the optimization results are sent to domain experts for evaluation. Finally, rule knowledge that can fully express the action is found.

5. Simulation and analysis

In order to verify the effectiveness of the flight action rule extraction method based on grey wolf optimization algorithm, the simulation analysis is carried out by taking horizontal right-turn and single plane loop as examples.

5.1. Knowledge extraction of horizontal right-turn maneuver rules

When the plane enters a horizontal right turn, it tilts to the right by a certain Angle from the flat flight state and continues until the course changes. The general variation trend of flight parameters in the turning process is shown in figure 4(a) below.

In the actual flight process, the flight parameters will vary due to the individual differences of pilots. As the real flight data are secret, the aircraft model is used in this paper to randomly generate the horizontal right-turn maneuver samples through Matlab 2017a, which are shown in figure 5(a). The negative samples used for rule extraction are composed of other maneuvers. The total data samples are 550, including 50 positive examples and 500 negative examples.

Number of grey wolf individuals \( m \) is set to 50. The total number of iterations \( \text{Maxgen} \) is set to 180. The dimension of grey wolf individual \( d \) is set to 28. The figure 6 shows the variation trend of fitness value of the optimal solution in the extraction process of flight action rules. It can be seen from the figure 6 that in the 100th generation, the optimal fitness value reaches the maximum, and the optimal grey wolf individual fitness value is 13.6104.
By optimizing of GWO, the optimal solution obtained is 0010000010000010000011010000, which contains the properties as follows:

$$K_3 > \Delta \psi_{\text{min}} = 95.16^\circ \quad \& \quad K_9 > (\sum |\Delta \phi|)_{\text{max}} = 73.176^\circ \quad \& \quad K_{15} < |\Delta h|_{\text{max}} = 10.2$$

$$\& \quad K_{21} < (\sum |\Delta \gamma|)_{\text{max}} = 3.02^\circ \quad \& \quad K_{22} < \gamma_{\text{max}} = 2.6^\circ \quad \& \quad K_{24} < \phi_{\text{max}} = 79.49^\circ$$

The knowledge of this rule includes the meanings as follows: The difference between the heading Angle at the ending time and the starting time is greater than 95.16°. The cumulative change of the minimum inclination Angle is greater than 73.176°. The absolute value of the height difference between the ending time and the starting time is less than 10.2m. The cumulative change of the pitch Angle is less than 3.02°. The maximum pitch Angle is less than 2.6°. The maximum inclination Angle is less than 79.49°.

Algorithm also gets the second optimal solution, and its code is 0000000001001100000001110000, which contains the properties as follows:
The knowledge means that the flight action can also be described as: the inclination angle is among (0, 79.49°). The normal overload is greater than 0 and the cumulative change is greater than 4.17. The maximum pitch angle is less than 2.6°. The cumulative change of the maximum inclination angle is less than 83.56°. As can be seen from the description of the first solution, its parameter attributes are mainly flight state parameters, which indicate that this rule is described from the perspective of flight state. As can be seen from the description of the second solution, its parameter attributes are mainly related to the flight control quantity. According to the flight dynamics equation, there is a functional relationship among the overload, inclination angle and pitch angle and the flight control quantity. Hence, the rule knowledge is described from the Angle of the flight control quantity.

The above two flight action rule knowledge are evaluated by the field experts, and it is considered that the extracted knowledge can meet the requirements when it is not required to accurately describe the horizontal right-turn maneuver. Meanwhile, the experiment indicates that the flight action rule knowledge extraction method proposed in this paper is effective.

5.2. Knowledge extraction of single plane loop action rules
In order to verify the effectiveness of the knowledge extraction method further, the single plane loop action is adopted. 550 single plane loop action samples are selected, including 50 positive examples and 500 negative examples. According to the method proposed in this paper, the relevant flight parameter attribute characteristic quantity of the single plane loop action is calculated statistically. The general trend of relevant flight parameters is shown in figure 4(b).

Figure 7. Optimal fitness value curve of single plane loop action extraction
According to the results of optimization, the optimal solution is coded as 100011000000010000110000000, which contains the properties as follows:

\[
K_{10} > \phi_{\min} = 0 \quad & \quad K_{13} > \left( \sum |\Delta n_i| \right)_{\min} = 4.17 \quad & \quad K_{14} > n_{\min} = 0 \\
& \quad K_{22} < \gamma_{\max} = 2.6^\circ \quad & \quad K_{23} < \left( \sum |\Delta \phi_i| \right)_{\max} = 83.56^\circ \quad & \quad K_{24} < \phi_{\max} = 79.49^\circ
\]

The meaning of the solution is: the height difference between the end time and the starting time is greater than 356.6m and less than 878.2m. The course angle difference between the end time and the starting time is equal to 0°, the cumulative change of the course angle is 0°, the cumulative change of pitch angle is greater than 0°.
278.46°, and the cumulative change of inclination Angle is 0. According to the evaluation of domain experts, the above two solutions are valid.

According to the evaluation function designed in this paper, since the total number of counter examples is fixed, the ability to exclude negative examples is the same, and the number of parameter attributes in the solution is also equal. Hence, this can lead to the non-unique solution of the algorithm. The correctness and validity of the solutions are evaluated by the domain experts, and the correct and effective rules are reserved.

6. Conclusion
Aimed at the bottleneck problem of the lack of combat related knowledge in UCAV autonomous air combat, this paper proposes a method to extract air combat knowledge from massive flight parameter data. For flight action rules knowledge extraction, the flight action rule extraction method based on grey wolf optimization algorithm is proposed. For this method, the wolf individual position update strategy and fitness evaluation function are redesigned, which make the number of solution attributes contained not too simple or redundancy. The feasibility and the effectiveness of the proposed method are validated by simulation. The extraction of flight action rules is the basis of the extraction of tactical rules. Hence, the extraction of tactical rules will be studied.

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References
[1] Wang, Y.J., Dong J., Liu, X.D., Zhang, L.X. (2015) Identification and standardization of maneuvers based upon operational flight data. Chinese Journal of Aeronautics, 28: 133-140.
[2] Wang, D.X., Hu, X.G., Liu, X.P., Huang, D.M. (2009) Attribute-oriented algorithm based on extended concept lattice. Journal of Shanghai Jiaotong University, 43: 476-478.
[3] Xie, C., Ni, S.H., Zhang, Z.L. (2005) Pattern attributes extraction of flight data based on rough set. Computer Engineering, 31: 169-172.
[4] Pal M., Foody G.M. (2010) Feature selection for classification of hyperspectral data by SVM. IEEE Trans on Geoscience and Remote Sensing, 48(4): 2298-2306.
[5] Miao, W., Liu, C.C., Geng Z. (2018) Statistical approaches for causal inference. Sci. Sin. Math., 48:1753-1778.
[6] Yin, W.J., Ni, S.H. (2006) A method of recognizing flight maneuver based on genetic algorithm. Computer Development & Applications, 324: 50-51.
[7] Su, C., Ni, S.H., Wang, Y.H. (2011) Method of rule acquisition of flight state based on improved AIS. Computer Engineering and Applications, 47: 237-239.
[8] Seyedail, M., Seyed, M.M., Aandrew, L. (2014) Grey wolf optimizer. Advances in Engineering Software, 69: 46-61.
[9] Nikzad-Khasmakhi, N., Balafar, M.A., Feizi-Derakshi, M. R. (2019) The state-of-the-art in expert recommendation systems. Engineering Applications of Artificial Intelligence, 82: 126-147.