Fast Calculation Method of UCAV Maneuver Flight Control Based on RBF Network

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Abstract. In order to solve the mathematical characterization and real-time generation of UCAV tactical maneuvers, a solution based on RBF network was proposed. Firstly, the characteristics and characterization methods of tactical maneuver trajectory are studied. An optimal control model of maneuvering trajectory is established and solved by genetic algorithm to generate sufficient neural network training samples. Secondly, based on the fitness function value and initial conditions as the input, and the key point control quantity of tactical maneuvers as the output, an air combat tactical maneuver trajectory rapid generation system based on RBF network was built. Finally, the RBF network is trained using the Recursive Least Squares (RLS) method. The training error was in the order of $10^{-5}$, which indicated that this method could realize the nonlinear mapping relationship between the fitness value and the trajectory with high accuracy. And through this network could quickly generate high-stability, UCAV executable maneuver trajectory.

1. Introduction
The autonomous air combat represents the direction of the future development of the Unmanned Combat Aerial Vehicle (UCAV). The air combat tactical maneuver modeling and rapid trajectory generation is one of the key technologies for realizing UCAV autonomous air combat. Modeling the tactical maneuver of UCAV and building an accurate and complete tactical maneuvering library for air combat is the basis of the planning and control of autonomous air combat maneuver.

For the problem of UCAV tactical maneuver modeling and rapid trajectory generation, there are fewer open literature available. The visible maneuvering decision literature[1,2] only uses the simplified fighter model for the design of the maneuver library. These models cannot reflect the true dynamic characteristics and tactical characteristics of the carrier and it is difficult to solve the problem of real-time maneuver generation under the consideration of dynamic characteristics and tactical characteristics[2][3], so it is not suitable for tactical maneuver modeling and UCAV real battle simulation.

Comprehensively considering the accuracy of tactical maneuver modeling and the rapidity of trajectory generation under multiple constraints, this paper analyzes the basic principles of tactical maneuvering modeling and proposes tactical maneuvering characterization methods and construction ideas. The UCAV kinetics model is established under multi-constrained conditions. The optimal control model of the maneuvering trajectory with the manipulated rate change rate as the optimization object and the flight control quantity solution scheme based on the genetic algorithm were designed. Focusing on the real-time problem of solving the flight control quantity in the wide-area state space,
the RBF neural network is introduced to achieve fast flight control and precision control of the maneuvering curve.

2. Basic Principles of UCAV Tactical Maneuver Trajectory Modeling

The UCAV tactical maneuver trajectory modeling problem is a process that determining the tactical maneuver trajectory and its state characteristics according to the launch capability of the weapon system, and then solving the flight maneuver amount, and solving the flight parameter calculation using the UCAV kinematics dynamic equation to complete the trajectory generation. The key to modeling is the mathematical representation of maneuvers and the calculation of flight control. Based on this, this paper designs the following modeling ideas:

Firstly, the tactical maneuver trajectory is mathematically characterized. According to the spatial position and state characteristics of the maneuvering trajectory, the trajectory key points or state characteristic parameters are set by a certain division rule. Based on the actual launch capability of the weapon system, the expected flight state control value of the critical point or state characteristic parameter is determined. Then, an optimal control model of the tactical maneuver trajectory is established. Through an optimization algorithm, the UCAV kinematics dynamic model is iterated and the flight control quantity is solved to obtain the desired flight state. In order to improve the speed of flight control, the neural network is introduced and the solution of the optimal control model of the trajectory is used as a priori sample to train the neural network. With the help of neural network's nonlinear mapping ability and fault tolerance, the nonlinear mapping relationship between initial state, performance index (fitness function) and maneuvering flight control amount is constructed. And through the training completed network, a fast output of the flight control is achieved.

3. UCAV kinetic model

In order to accurately describe the geometry of the maneuvering trajectory and the motion characteristics of the UCAV, a fine three degree of freedom motion dynamics model is established. The parameters of the model are defined as shown in figure 1.

The flight control and the state variables are respectively defined as $[\alpha, \mu, \delta]^T$ and $[x, y, h, \gamma, \psi, m]^T$, the UCAV kinetic model can be expressed as[4]:

$$
\begin{align*}
\dot{x} &= v_c \cos \gamma \sin \psi + \dot{W}_x \\
\dot{y} &= v_c \cos \gamma \cos \psi + \dot{W}_y \\
\dot{h} &= v_c \sin \gamma + \dot{W}_h \\
\dot{v}_a &= \frac{T \cos \alpha - D}{m} - g \sin \gamma - \dot{W}_x \cos \gamma \sin \psi - \dot{W}_y \cos \gamma \cos \psi - \dot{W}_h \sin \gamma \\
\dot{\gamma} &= \frac{(L + T \sin \alpha) \cos \mu}{mv_a} - \frac{g}{v_a} \cos \gamma + \frac{\dot{W}_x \sin \gamma \sin \psi}{v_a} + \frac{\dot{W}_y \sin \gamma \cos \psi}{v_a} - \frac{\dot{W}_h \cos \gamma}{v_a} \\
\dot{\psi} &= \frac{(L + T \sin \alpha) \cos \mu}{mv_c \cos \gamma} + \frac{\dot{W}_x \sin \gamma}{v_c \cos \gamma} - \frac{\dot{W}_y \cos \psi}{v_c} - \frac{\dot{W}_h \sin \psi}{v_c} \\
m &= -c_T T = \delta T_{\max} (\nabla_h, h_c), L = \frac{1}{2} \rho v_a^2 S C_L, D = \frac{1}{2} \rho v_a^2 S C_D
\end{align*}
$$

In the formula: $(x, y, h)$ represents the position of UCAV in the inertial coordinate system; $v_c$ is the UCAV vacuum speed; $(\gamma, \psi, \mu)$ represents the track inclination angle, track declination angle, track roll angle; $\alpha$ is the angle of attack; $m$ is the quality of UCAV; $g$ is the acceleration of gravity; $(T, D, L)$ represents respectively Thrust, air resistance, lift; $(\dot{W}_x, \dot{W}_y, \dot{W}_h)$ and $(\dot{W}_x, \dot{W}_y, \dot{W}_h)$ represent the components along the axis for wind speed and wind acceleration; $\rho = 1.225 \frac{\text{slug}}{\text{ft}^3}$ means the air density; $S$ is the reference cross-sectional area for UCAV; $C_L, C_D$ represents the lift coefficient and drag coefficient,
respectively; $c$ represents the fuel consumption coefficient; $\delta$ represents the throttle setting; $T_{\text{max}}$ is the maximum for the engine thrust.

In order to ensure that the platform of the tactical maneuver is flight-ready, the UCAV should meet the constraints of the UCAV flight envelope, and literature [5] discusses this issue in detail.

![UCAV kinematic model parameter diagram](image)

**Figure 1.** UCAV kinematic model parameter diagram

### 4. Modeling of UCAV Tactical Maneuver Trajectory Optimal Control Problem

#### 4.1. Mathematical characterization of maneuvering trajectory

In order to give full play to the occupant advantage and attack characteristics of tactical actions, when considering the mathematical representation of maneuvers, the spatial and non-spatial characteristics of the maneuver should be comprehensively considered, and key points and state characteristic parameters should be used to describe them.

**4.1.1. Key point.** The key point refers to the spatial position of the state parameter that needs to be judged during maneuvering. The UCAV flight control system uses a series of manipulations to make the state parameter meet the requirements of the standard state at the key point, and then completes a standard maneuver[2].

When the key points are divided, according to the spatial geometry of the maneuvering trajectory, the complete maneuvering motion is decomposed into several trajectory fragments by the track state Angle. Select the track status Angle between the broken track fragments and the fragments as the key points of the maneuvering marks. The key points should be guaranteed to cover the end point of the maneuver trajectory and the intermediate state point to realize the full identification of the maneuver trajectory. The flight state control amount and the range of state parameters the UCAV needs to approach should be set at key points.

**4.1.2. State characteristic parameters.** The state characteristic parameters are used to characterize the non-spatial characteristics of the UCAV tactical maneuver trajectory, such as the closing window of the engine, the maneuver entry and exit time, and the characteristic requirements that need to be met from the initial state to the maneuver ready state. For the loop maneuvers, in order to overcome the maneuvering slowness of entering the manoeuvre, which results in the dynamic situation where the UCAV climbs too high or the high point speed is too low, it is necessary to ensure that the normal overload is formed within the time after the abutment is implemented. Therefore, the transition time from the initial state into the suitable overload is taken as the state characteristic parameter.

**4.2. UCAV tactical trajectory optimal control model**

**4.2.1. The method of division and construction of the trajectory.** The tactical maneuvers are divided into tract segments connected to each other based on trajectory characteristics[6]. Each segment maintains the same rate of change of the manipulated variable, and the manipulated variable rate of change is regarded as the optimization parameter in the entire process, denoted as $f$. 
The termination condition of the track fragment is:

\[ \psi = |X_{n_f} - X_{n_i}| < \xi \]  

(2)

In the formula, \( X_{n_f} \) and \( X_{n_i} \) represented the state vector of the \( m \) th track fragment and the termination moment respectively.

4.2.2. Performance indicator function design. In order to eliminate the gap between the various parts of the function due to different dimensions or orders of magnitude and the impact on the overall performance index function, the three parts of the performance index function are normalized. The specific expressions of the performance indicator function are as shown in equation (3).

\[
J = \min(\sum_{i=1}^{n} r_i P_i(X) + \omega_1 \sum_{i=1}^{n} q_i T_i + \omega_2 \sum_{i=1}^{n} j_i F_i), s.t. \sum_{i} \omega_i = 1 \, \omega_i \geq 0, i = 1, 2, 3
\]  

(3)

In the formula, \( n \) represents the number of key points; \( m \) represents the number of trajectory segments; \( l \) represents the number of state characteristic parameters; and \( \omega \) is a weight coefficient of each part of the function. The \( P_i(X) \) represents the penalty function that the \( i \) th key point beyond the standard constraint; \( T_i \) is the penalty function that represents the \( k \) th state property, which exceeds the standard constraint. \( F_i \) means the normalized representation of the difference in the rate of change of manipulated volume for adjacent track segments.

4.2.3. Genetic Algorithm Based Solution Strategy. In the solution, a decimal encoding method is used to match the manipulation rate change sequence to the gene segment on the chromosome. Initial samples are randomly generated within the range of manipulated value change rate, selection strategy is used for selection operation, and adaptive strategy is used for crossover and mutation operation, so that the crossover and mutation probability can be self-adaptive changed based on the degree of population fitness. Those method are used to maintain population diversity, and avoid falling into the local optimal solution to the maximum extent possible.

Due to the sequential selection strategy, the greater the individual fitness value is, the higher the selection probability is. Therefore, the genetic algorithm is suitable for solving the maximum of the fitness function. From the expression of formula (3), we can see that the performance index function is non-negative and always greater than zero, so the reciprocal of the performance index function is used as the fitness function, defined as:

\[
fitness = \frac{1}{J}
\]  

(4)

The fitness function represents the degree of approximation of the maneuvering trajectory to the standard maneuvering curve. In theory, the greater the fitness function value, the higher the degree of approximation to the standard curve.

5. Method for predicting flight control quantity based on RBF neural network

In order to improve the fastness of genetic algorithm for flying maneuver quantity, this section will introduce RBF neural network, and design a method for rapid prediction of maneuvering flight maneuver quantity based on fitness function as a prediction and evaluation criterion. Using the neural network's nonlinear mapping ability, the mapping relationship of the initial state, fitness function value and flight control amount is constructed to achieve rapid prediction of the flight control amount. The fitness function value is used as the quantification standard for the approximation of the maneuvering curve, and the precision control of the maneuvering curve is achieved.

5.1. Determination of RBF Network Structure

The RBF network includes three layers of input, hidden and output layers. According to the function approximation theory, any function can be expressed as a weighted sum of a set of RBFs. The topology of the RBF neural network implements a weighted combination of different basis functions
through adjustment of the weight threshold and the basis of the basis function, thereby achieving the approximation of the objective function[8]. In order to quantify the degree of approximation of the maneuvering trajectory and satisfy the wide-area state space requirements for practical applications of the maneuvering trajectory, the fitness function value and the maneuver initial state are taken as the predicted input values of the RBF neural network, and the output value of the network is corresponding to a set of manipulated variable rate of change sequence that implements the maneuver. Assuming that the initial moment of the maneuvering implementation is always a straight-line state, the initial state quantities affecting the maneuver implementation can be reduced to the two main state quantities: initial altitude and initial flying speed. Therefore, the RBF neural network constructed has three neurons in the input layer: fitness function value $f_{\text{fitness}}$, initial flight altitude $h_0$, and initial flying speed $v_{\text{u}_0}$. The output layer is a set of manipulation rate change rate series $v_{f_j}$. Each neuron represents a component of the sequence, denoted as $f_j, j = 1, 2, \cdots, N$. $N$ is the length of the manipulated variable rate sequence, that is, the number of neurons in the output layer, and the specific number is related to the division of the maneuver trajectory described in Section 4. The basic topology of RBF neural network is shown in figure 2.

![Figure 2. Topology structure of RBF neural network](image)

### 5.2. RBF neural network training

The Gaussian function is selected as the radial basis function. The radial basis function of the hidden layer of the RBF neural network as the activation function can be expressed as:

$$ R(X_p - C_i) = e^{-\frac{1}{2\sigma^2}||X_p - C_i||^2} $$

In the formula, $||\cdot||$ means the Euclidean norm, $C_i$ is the center of the Gaussian function; $\sigma$ is the variance of the Gaussian function, the network output can be:

$$ f_{v_j} = \sum_{i=1}^{H} w_{i,j} e^{-\frac{1}{2\sigma^2}||X_p - C_i||^2}, \quad j = 1, 2, \cdots, N $$

In the formula, $X_p = (f_{\text{fitness}}, h_0, v_{\text{u}_0})^T$ is the $p$ th input sample; $p = 1, 2, \cdots, P, P$ is the total number of samples; $C_i$ is the center of the network hidden layer nodes; $w_{i,j}$ is the connection weight from the hidden layer to the output layer; $i = 1, 2, \cdots, H, H$ is the number of hidden layer neurons; $f_{v_j}$ is the actual output of the $j$ th output node; $j = 1, 2, \cdots, N, N$ is the number of output layer neurons.

The network learning process includes two stages: hidden layer neuron learning and output layer neuron learning. The hidden layer neurons use unsupervised $K$-means learning clustering method[7] to determine the center value $C_i$ and variance $\sigma_i$ of each node's basis function; the output layer neurons use supervised learning when learning, and adopt the recursive least squares (RLS) method[7]. When the difference
between the actual output of the network and the expected output tends to be optimal in the least-squares sense, the network learning is terminated and the connection weights $w_{ij}$ from the hidden layer to the output layer are output.

6. Model verification and simulation analysis

The paper uses a certain UCAV platform and performance data, ignores the influence of the wind field, and uses the loop maneuvering as an example for simulation verification. According to the maneuvering and data generation methods described above, 60,000 sets of maneuverability data are generated for network training. The number of input layer neurons is 3, and the number of output layer neurons is 36, which represents a set of 36 sequence of angle-of-attack rates. According to Kolmogorov's theorem, considering the learning speed and generalization ability of RBF network, the number of neurons in the hidden layer is finally determined to be 65.

The error convergence curve in the neural network training process is shown in figure 3.

![Figure 3. The convergence curve of the error of RBF neural network](image1)

From figure 3, we can see that after the 40th training, with the input of training samples, the difference between the expected output and the actual output of the network gradually becomes smaller, and finally tends to be stable, that is, the parameters have reached the neighborhood of the optimal solution, it shows that the network learning is very fast. As training progresses, the error converges to $5.17 \times 10^{-3}$. Proving that the network has achieved high convergence accuracy.

Using the trained neural network, randomly input the initial velocity, altitude, and fitness values, perform 200 Monte Carlo simulations, output the predicted value of the manipulated variable rate of change, and substitute the predicted value into the UCAV kinetics model for the flight parameter solution. Calculate the actual fitness value and compare the error effect compared to the expected value of the fitness value to verify the prediction effect of the network on the fitness value and the control ability of the fitness value on the accuracy of the maneuvering curve. The error rate of the fitness absolute error value compared to the expected fitness value is shown in figure 4. In figure 4, under 200 random initial conditions, the maximum error rate of the real fitness of network output compared with the expected fitness value is 9.808%, and the minimum error is 0.168%; The average error rate is kept within 5%, which indicates that this method can better control the precision of the maneuvering curve through the fitness value. Taking into account the larger output dimension, this error meets the general requirements of engineering applications.

Randomly select two sets of initial height and velocity values, and two sets of fitness function values to check the true spatial pattern of the network output values. The solution results are shown in figure 5. As can be seen from figure 5, in each initial state, the network output value can complete the status characterization of the loop maneuver and meet the tactical requirements of the maneuvering action. With different values of fitness function, there are certain differences in the spatial form of
maneuvering motion, satisfying the spatial arbitrariness and randomness demand of the maneuvering curve.

Due to the elimination of a huge amount of on-line calculations, the time required to calculate the flight control amount is greatly reduced compared to the genetic algorithm, and the generation time is kept within the range of 0.05s, it meets the rapidity of maneuver generation.

7. Conclusion

In this paper, the construction method and idea of the maneuvering trajectory model are proposed, and the optimal control model of the maneuvering trajectory is designed based on the change rate of manipulated variable. Based on RBF neural network, a fast solution method for maneuvering flight maneuver with fitness function as prediction and evaluation criteria is proposed. The quick solution to the flight control and the precision control of the maneuvering trajectory are realized, which provides a new idea for the tactical maneuver modeling problem and the design of maneuvering motion library.

![Figure 5. UCAV space flight trajectory solution results](image)

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