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Flight Attitude Stability Prediction and Evaluation of UAVs Based on LSTM

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ABSTRACT

This study aims to construct a high-precision, real-time UAV flight attitude stability prediction and evaluation system to solve the core problems of insufficient accuracy and poor real-time performance of traditional prediction methods. This is particularly significant for UAVs integrated with flexible textile sensors or those performing structural health monitoring of high-strength fiber-reinforced composite airframes. First, key attitude parameters such as pitch angle, roll angle, and yaw angle, as well as environmental data, are collected through multi-sensor fusion technology. After cleaning, feature extraction, and standardization preprocessing, a multi-layer LSTM prediction model combined with an attention mechanism is constructed. A multi-step rolling prediction strategy and a grid search-cross-validation hyperparameter optimization method are adopted. At the same time, a multi-dimensional stability evaluation framework covering indicators such as angular velocity variance, attitude deviation, and prediction error is established. Experimental results show that the proposed LSTM model significantly outperforms traditional ARIMA and other models in attitude prediction, reducing RMSE and MAE by 8.82% and 10.22%, respectively. It exhibits optimal prediction accuracy, particularly within the 25°-40° dive angle range, and effectively captures the temporal dependencies of attitude data. This study provides a scientific basis for optimizing UAV attitude control. Meanwhile, it holds significant theoretical and engineering value for improving fault early warning mechanisms.

KEYWORDS

Long Short-Term Memory, UAV, flight attitude, stability prediction, smart textiles

INTRODUCTION

With the rapid development of UAV technology and the continuous expansion of its application fields, UAVs are playing an increasingly important role in many fields such as military reconnaissance, civilian surveying and mapping, agricultural monitoring, and logistics distribution. As a typical nonlinear, strongly coupled, and underactuated system, the flight state of a UAV is affected by factors such as system structure and external interference, and the design of the control system still faces many challenges [1]. As a key component of the flight control system, attitude control plays a crucial role in maintaining the flight state of the UAV [2]. Specifically, in the field of modern smart textiles, UAVs equipped with flexible textile sensors are being used for remote atmospheric monitoring, while in the structural health monitoring of large-scale textile membrane structures and high-performance fiber-reinforced composites, UAVs provide an efficient automated inspection method.

Attitude control is the key to maintaining the stability and flexibility of the UAV during flight. By quickly and accurately measuring the angular velocity of the UAV, the UAV can adjust its attitude in a timely manner, respond to external interference, and maintain the stability and accuracy of flight [3]. UAVs need to quickly and accurately adjust their pitch, yaw, and roll attitudes to respond to flight mission requirements. Unstable attitude control may lead to flight instability, damage to the aircraft, or loss of control [4]. In practical applications, the instability of flight attitude greatly affects the quality of the acquired image data [5].

Traditional UAV attitude control methods mainly rely on PID control, active disturbance rejection control, and model predictive control. While these methods perform well under certain conditions, they often fail to achieve ideal control results when faced with complex and ever-changing flight environments and uncertain disturbances. With the rapid development of artificial intelligence technology, prediction models based on deep learning have provided new solutions for UAV attitude stability analysis. LSTM (Long Short-Term Memory) networks, as a type of neural network specifically designed for processing time-series data, can effectively capture the time dependencies in UAV attitude data, providing strong technical support for attitude stability prediction. By constructing an LSTM-based UAV flight attitude stability prediction model, we can not only identify potential attitude instability factors in advance but also provide a scientific basis for optimizing the attitude control system, which has significant theoretical and practical value for improving UAV flight safety and mission execution efficiency.

The core objective of this research is to construct a UAV flight attitude stability prediction and evaluation system based on LSTM networks, achieving accurate prediction and comprehensive stability assessment of UAV attitude changes during flight through deep learning technology. This research aims to address key issues such as insufficient accuracy and poor real-time performance of traditional prediction methods when processing attitude data from UAVs in complex flight environments.

The research content covers multiple levels of technical development and theoretical analysis. In terms of model construction, through in-depth analysis and improvement of the LSTM network structure, a prediction model architecture suitable for processing multi-dimensional UAV attitude data is established. The model will focus on the temporal prediction capability of key attitude parameters such as pitch, roll, and yaw angles, while also considering the impact of dynamic factors such as flight speed and altitude changes on attitude stability. The research will employ a multi-step rolling prediction method to better capture the temporal variation patterns of flight parameters, improving the accuracy and effectiveness of prediction.

In terms of constructing a stability evaluation system, the research will establish a multi-dimensional evaluation framework that comprehensively considers prediction accuracy, effectiveness, and stability. By comparing and analyzing the performance of the LSTM model with the traditional ARIMA model and other deep learning methods in attitude prediction, the superiority of the proposed method is verified. The research will also explore the combined application of attention mechanisms and LSTM networks to further enhance the model's ability to identify and process key attitude features. Through verification and analysis of actual flight data, it will provide theoretical support and technical guidance for improving the safety of UAV automatic flight control systems and perfecting fault warning mechanisms, thus promoting the development of UAV autonomous flight capabilities in complex environments.

LITERATURE REVIEW

Current Status of UAV Flight Attitude Research

UAV flight attitude control technology has developed into a relatively complete theoretical system and practical solutions after many years of development. Current research mainly focuses on improving attitude control accuracy, enhancing anti-interference capabilities, and the integrated application of multiple control strategies [6]. Traditional UAV attitude control relies on GPS systems for assisted navigation, but this has significant errors in the precise positioning applications of small UAVs. To overcome this limitation, researchers have begun to explore multi-sensor fusion technology, combining inertial navigation systems and visual sensors to provide redundancy guarantees for position estimation [7,8].

Attitude control is one of the core challenges in UAV navigation. UAVs need to quickly and accurately adjust their pitch, yaw, and roll attitudes to respond to flight mission requirements. Flight stability includes three dimensions: longitudinal, lateral, and directional stability. Sensors, as the core of data processing and flight control, are mainly responsible for collecting data from various sensors and calculating the aircraft attitude through comprehensive processing to achieve stable flight control8]. Current UAV attitude control research can be divided into three categories: linear control, nonlinear control, and intelligent control [9].

In terms of control strategies, model predictive control methods have been widely used. To address the actuator input constraints and unknown external disturbances faced by quadcopter UAVs during flight, researchers have designed an attitude stabilization control method with input constraints and disturbance compensation [10]. This method estimates unknown external disturbances by designing a wind disturbance observer and designs an optimal control law with a disturbance compensation law around the cost function. The flight control system, based on different control strategies such as PID controllers and model predictive controllers, achieves stable flight and precise control of the aircraft through real-time monitoring and feedback control [11]. These theories provide important support for improving the flight performance of UAVs and expanding their application fields.

Application of Predictive Models in the Aviation Field

Predictive models are increasingly widely used in the aviation field, providing important support for the safe operation and performance optimization of aircraft. From traditional mathematical modeling methods to modern machine learning technology, the development of predictive models has brought revolutionary changes to aerospace engineering [12].

In modern aviation, the application of prediction models covers multiple aspects, from flight dynamics modeling to trajectory prediction algorithm design and optimization. Research on quadrotor UAV trajectory prediction methods mainly focuses on flight dynamics modeling, trajectory prediction algorithm design and optimization, and incorporates advanced technologies such as deep learning [13]. The introduction of deep learning technology enables prediction models to better handle complex nonlinear relationships and temporal dependencies, especially showing significant advantages when processing large amounts of flight data. Using a total station to compare relative distance measurements of the UWB module, millimeter-level accuracy relative distance verification data [14] is provided. This high-precision measurement technology provides a reliable data foundation for the training and validation of the prediction model.

Predictive models in the aviation field are also applied in aircraft stability analysis and control system design. While blade element and surface element methods in numerical simulations may not be suitable for propeller slipstream analysis and high-precision aerodynamic derivative calculations, high-precision numerical simulation methods can obtain aerodynamic coefficients and establish flight dynamics models for vertical takeoff and landing (VTOL) UAVs based on six-degree-of-freedom equations [15]. These predictive models can not only analyze pitch, roll, and yaw stability during hovering, VTOL, cruise, and transition states, but also provide a scientific basis for control design and evaluation. With the improvement of computing power and continuous optimization of algorithms, the application prospects of predictive models in the aviation field will be even broader.

THEORETICAL BASIS OF LSTM NETWORKS

LSTM Network Structure and Principles

Composition of LSTM Units

The structural design of LSTM units is the core of their excellent performance in time-series data processing. As a special recurrent neural network unit, LSTM effectively solves the gradient vanishing problem in long sequence processing of traditional RNNs through ingenious gating mechanisms and cell state design [13]. Each LSTM unit contains three gating structures and two states. These components work together to achieve selective memorization and forgetting of time-series information.

An LSTM unit mainly consists of an input gate, a forget gate, an output gate, and cell states [15]. The input gate controls how much new information can be written into the memory unit, determining how the input at the current moment is processed and stored. The forget gate controls how much information in the memory unit at the previous moment needs to be discarded; this mechanism allows the network to actively forget unimportant historical information. The output gate determines which information is output from the memory unit at the current moment, generating the final hidden state by filtering the cell states [16].

The cell state, as the memory carrier of the LSTM, stores important information from all moments in the sequence. Data flows into the cell state through the input gate and selectively discards irrelevant information through the forget gate; the cell state is constantly updated and changed throughout the process [15]. This design allows the LSTM to selectively "remember" important components of the time series problem and "forget" irrelevant information, thereby maximizing the transmission of key information [14].

The mathematical expression of the LSTM unit reflects the coordinated operation of the various gating mechanisms. The activation values of the forget gate, input gate, and output gate are calculated using the following formulas:

$$f_t = \sigma_s(W_f x_t + U_f h_{t-1} + b_f) \tag{1}$$

$$i_t = \sigma_s(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$o_t = \sigma_s(W_o x_t + U_o h_{t-1} + b_o) \tag{3}$$

Where σ_s represents the sigmoid activation function, W, U is the weight matrix, b is the bias vector. Cell state updates are accomplished jointly through the input gate and the forget gate, while the final hidden state is determined jointly by the output gate and the cell state.

Backpropagation Algorithm

The backpropagation algorithm in LSTM networks is the core mechanism for network learning and parameter optimization. It updates weights by calculating the gradient of the loss function relative to the parameters of each layer. Unlike traditional neural networks, the backpropagation process of LSTM has obvious temporal characteristics and needs to handle the gradient propagation problem in the time dimension. The implementation of this algorithm involves complex gradient calculation and parameter adjustment strategies, which plays an important role in improving the accuracy of the model in predicting the attitude stability of UAVs.

In the training process of LSTM networks, error backpropagation and gradient descent are key steps to correct and optimize network weights. This process starts with the calculated error and updates the parameters in the network through the backpropagation mechanism. Unlike the backpropagation of standard neural networks, this process of LSTM exhibits bidirectional characteristics: on the one hand, the error is propagated backward sequentially along the time series; on the other hand, the error is also propagated between different layers of the network [17]. Gradient calculation requires consideration of parameter updates for the forget gate, input gate, and output gate. Each gated unit affects the final gradient contribution.

For the temporal characteristics of UAV attitude data, the LSTM backpropagation algorithm needs to handle the gradient propagation problem of long-term dependencies. The algorithm unfolds the time series using the BPTT method and calculates the gradient contribution at each time step. The gradient update formula can be expressed as:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L(\theta_t) \tag{4}$$

Where θ represents network parameters, η is the learning rate, L where is the loss function. This formula describes the update rule of the parameters in each iteration, ensuring that the network can gradually converge to the optimal solution. Through accurate gradient calculation and reasonable learning rate settings, the backpropagation algorithm can effectively improve the LSTM model's ability to predict UAV flight attitude, providing a reliable data foundation for subsequent stability analysis.

Advantages and Disadvantages of LSTM

Long Short-Term Memory (LSTM) neural networks show significant advantages over traditional recurrent neural networks in processing time-series data. Compared with RNNs, LSTM is not affected by gradient vanishing and exploding problems, has greater flexibility in processing complex time series, and can fully mine the temporal information of the data to improve the prediction accuracy of the algorithm. This network architecture effectively controls the flow of information through a gating mechanism, enabling the model to maintain a long-term memory state, and performs excellently in tasks such as UAV flight attitude prediction that require consideration of historical states.

Compared with simple feedforward networks, LSTM networks have unique advantages in terms of model temporal correlation [18], which makes LSTM very suitable for tasks that require consideration of a large amount of historical information [19]. In the field of UAV trajectory prediction, LSTM network models exhibit relatively small absolute errors and strong timeliness, providing a certain reference for air combat trajectory prediction. When a UAV's flight trajectory undergoes abrupt changes, LSTM can effectively suppress the sharp increase in prediction error, maintaining high prediction stability.

Although LSTM performs well in time series prediction, it also has some shortcomings. A drawback of LSTM is that it does not directly optimize for sequence-to-sequence mapping, thus it may perform worse than other specially optimized models on certain tasks. LSTM typically has a large number of parameters, resulting in potentially longer training times. In practical applications of UAV attitude prediction, the computational complexity and training cost of the model need to be balanced with prediction accuracy. In specific scenarios of UAV flight attitude stability prediction, these characteristics of LSTM dictate that its actual deployment requires a comprehensive consideration of the balance between prediction accuracy, computational efficiency, and real-time requirements.

Advantages of LSTM in Temporal Data Prediction

Advantages Compared to Traditional Neural Networks

Traditional recurrent neural networks (RNNs) face serious problems of vanishing and exploding gradients when processing temporal data. LSTM, through its unique gating mechanism, effectively solves these technical challenges. The core idea of LSTM is to add forgetting gates and cell state structures to the recurrent neural network, enabling the model to simultaneously possess memory and forgetting characteristics over a long period, thus effectively solving the gradient explosion and vanishing gradient problems and flexibly processing long-sequence temporal data.

Compared to simple feedforward networks, LSTM networks have unique advantages in terms of model temporal correlation. As a variant of RNN, LSTM neural networks, by introducing gating units such as input gates, forget gates, and output gates, can selectively retain and delete information, effectively overcoming problems such as gradient vanishing in RNNs. They perform better than RNNs in tasks involving long-distance information dependencies and are often used for processing and preserving long-term temporal information. In the field of UAV attitude prediction, traditional neural networks often struggle to capture long-term dependencies in flight data, while LSTM, with its sophisticated processing units, can effectively handle complex time-series patterns. The feature parameters in UAV flight data are temporal data with strong temporal correlation. To better capture the features of time series and better learn the dependencies between time series, the LSTM network structure is used as the encoding and decoding layers in the AE (Autoencoder), thus preserving the temporal information in the feature parameters. Trajectory data has spatiotemporal characteristics and is a typical time-series data. LSTM is suitable for processing and predicting time-series data and can alleviate the problems of gradient vanishing and gradient exploding.

Through precise control of the gating mechanism, LSTM can dynamically adjust the information flow according to the importance of the input data. This adaptive characteristic makes the model more robust and accurate in handling complex flight attitude changes of UAVs.

Multi-Dimensional Data Processing Capability

Attitude data generated during UAV flight has typical multi-dimensional characteristics, including three basic attitude parameters such as pitch angle, roll angle, and yaw angle, as well as multiple related variables such as angular velocity, acceleration, altitude, and velocity. LSTM networks exhibit unique technical advantages in processing this type of multi-dimensional time-series data, and can simultaneously capture the interrelationships between different dimensions and the time-series characteristics of each dimension.

In the multi-dimensional data processing architecture, LSTM networks achieve parallel processing and fusion analysis of data from different dimensions by constructing a multi-input gating mechanism. The cell state update formula inside the network can be expressed as:

$$\mathrm{C_t} = \mathrm{f_t} \odot \mathrm{C_{t-1}} + \mathrm{i_t} \odot \tilde{\mathrm{C}}_\mathrm{t} \tag{5}$$

Where $\mathrm{C_t}$ represents the current cell state, $\mathrm{f_t}$ is the forget gate output, $\mathrm{i_t}$ is the input gate output, $\tilde{\mathrm{C}}_\mathrm{t}$ is the candidate value vector. This design allows the network to selectively retain and update important information from different dimensions, while filtering out redundant or noisy data.

The processing weights for different data dimensions are shown in Table 1.

Table 1. Processing Weights for Different Data Dimensions

Data Dimensions	Data Types	Sampling Frequency	Data Precision	Processing Weights
Pitch Angle	Angle Value	100Hz	0.01°	0.3
Roll Angle	Angle Value	100Hz	0.01°	0.3
Yaw Angle	Angle Value	100Hz	0.01°	0.25
Altitude	Distance Value	50Hz	0.1m	0.15

Compared with traditional single-dimensional prediction methods, LSTM's multi-dimensional processing capability can more accurately reflect the complexity of UAV attitude changes. The network learns the coupling relationships between data from different dimensions to establish a more complete attitude prediction model. This processing method not only improves prediction accuracy but also enhances the model's ability to identify anomalies, providing more reliable technical support for UAV flight safety. In practical applications, the multi-dimensional data processing capability enables LSTM networks to maintain high prediction stability in complex flight environments, especially when dealing with multivariate coupled attitude control problems.

Practicality of Model Training

The practicality of LSTM models in UAV attitude prediction is reflected in their efficient training process and good engineering application characteristics. Model training needs to make full use of available historical data. In UAV attitude stability prediction, time series data is the main data source, and the data needs to be divided according to time order to ensure the chronological order of training and validation data. Typically, the dataset can be divided into training set, validation set, and test set, where the training set is used for updating model parameters, the validation set is used for adjusting hyperparameters, and the test set is used for evaluating the final model performance.

In practical engineering applications, the training efficiency of the LSTM model directly affects the system's response speed and deployment cost. According to the needs of different application scenarios, the model parameter configuration can be flexibly adjusted to achieve a balance between computing resources and prediction accuracy. During training, the selection and adjustment of hyperparameters are crucial. Hyperparameters include learning rate, batch size, number of layers, and number of nodes in the model. The learning rate determines the update speed of model parameters; an excessively large learning rate may lead to oscillations, while an excessively small learning rate will slow down the model's convergence speed.

The practicality of model training is also reflected in its adaptability to different data qualities. During model training, it is necessary to select a suitable dataset and preprocess it, including data cleaning and data normalization. In this way, the LSTM model can achieve good prediction results with limited computing resources, providing reliable technical support for UAV attitude stability analysis.

UAV ATTITUDE DATA ACQUISITION AND PREPROCESSING

Data Acquisition Methods

Data Source Selection and Introduction

The quality of UAV flight attitude data directly determines the accuracy and reliability of the LSTM prediction model. This study selected multiple types of data sources to ensure the comprehensiveness and representativeness of the training data. The main data sources include actual flight test data, simulation platform-generated data, and public datasets (Table 2). These three types of data sources each have their own characteristics and can provide rich training samples for the model. In the comparative evaluation with the ARIMA model, we uniformly used a mixed validation set containing real flights and high-fidelity simulations. To eliminate bias caused by distribution differences across data sources, all input data underwent rigorous Z-score normalization (see Equation 9) before modeling, ensuring that the model learns the physical essence of attitude evolution rather than specific data noise.

Table 2. Different Data Sampling Frequencies

Data Source Type	Data Volume (Hours)	Sampling Frequency (Hz)	Main Features
Actual Flight Tests	25.6	100	High Realism, Multi-Scenario Coverage
Simulation Platform Data	156.8	200	Large Data Volume, Controllable Parameters
Public Dataset	89.3	50-150	Standardized, Facilitating Comparison and Verification

Actual flight test data is the core data source of this study. Real attitude parameters are obtained through actual flight of the multi-rotor UAV. The flight tests cover various flight modes, including typical scenarios such as hovering, cruising, and maneuvering flight. During data acquisition, the focus is on the variation patterns of three key attitude angles: pitch angle, roll angle, and yaw angle. Simultaneously, corresponding environmental parameters such as flight speed, altitude, and wind speed are recorded. The test data has high realism and can reflect the attitude change characteristics of the UAV in the actual flight environment, but the data volume is relatively limited and the acquisition cost is high.

Simulation platform data serves as an important supplementary data source, generating a large number of attitude data samples through professional UAV flight simulation software. The advantage of simulation data lies in its ability to simulate various extreme flight conditions and fault scenarios, providing rich boundary condition training samples for the model. The simulation platform can precisely control various flight parameters and environmental conditions, generating standardized data formats to facilitate subsequent data preprocessing and feature extraction. Although simulation data has certain limitations in terms of realism, its large data volume and wide coverage effectively compensate for the shortcomings of experimental data.

Public datasets provide important benchmark data for model validation and comparative analysis. These datasets usually undergo rigorous quality control and standardization, and have good data integrity and consistency. Public datasets can be used to verify the generalization ability of the constructed LSTM model and to make objective comparisons with other research results.

Data Acquisition Equipment and Deployment

Accurate acquisition of UAV attitude data is a fundamental step in building an LSTM prediction model. This study adopts a multi-sensor fusion approach, using core equipment such as inertial navigation systems, gyroscopes, and accelerometers to complete real-time monitoring of attitude parameters.

The inertial navigation system quickly and accurately measures the angular velocity of the UAV, enabling it to adjust its attitude in a timely manner, respond to external disturbances, and maintain flight stability and accuracy. The gyroscope is responsible for measuring the angular velocity changes of the UAV in three axes; especially in high-dynamic environments, the gyroscope can provide crucial attitude change information. The accelerometer is used to measure the linear acceleration of the UAV, and together with the gyroscope data, it can more comprehensively describe the motion state of the UAV.

It should be noted that the 100Hz sampling frequency of the Yaw angle in Table 1 originates from the high-frequency attitude update of the IMU gyroscope. Due to the lower update frequency of the GPS module (10Hz), a loose coupling strategy based on Kalman filtering was adopted in the actual system. This strategy utilizes low-frequency GPS data to correct the accumulated deviation from high-frequency attitude integration in real-time, thereby ensuring the long-term reliability of the input data for the prediction model.

As shown in Table 3, the equipment deployment scheme considers the UAV's center of gravity balance and electromagnetic compatibility issues. The main sensor modules are installed at the UAV's geometric center of gravity to reduce the impact of airframe vibration on measurement accuracy. The data acquisition system uses an STM32 microcontroller as the core processing unit, responsible for the synchronous acquisition, preprocessing, and storage of sensor data. The system is designed with a high-frequency sampling rate of 1000Hz, capable of capturing subtle attitude changes of the UAV under various flight conditions.

Table 3. Equipment Deployment Scheme

Sensor Type	Measurement Range	Accuracy	Sampling Frequency	Deployment Location
Three-Axis Gyroscope	±2000°/s	±0.1°/s	1000Hz	Aircraft Center of Gravity
Three-Axis Accelerometer	±16g	±0.01g	1000Hz	Aircraft Center of Gravity
Magnetometer	±49Gauss	±0.1°	100Hz	Away from Electromagnetic Interference Areas
GPS module	Global Coverage	±3m	10Hz	Top of Aircraft

To ensure the continuity and integrity of data, the system is configured with a dual redundant storage mechanism and real-time data transmission function. When the UAV is in a complex flight environment or encounters external interference, the multi-sensor fusion algorithm can automatically detect abnormal data and correct it, providing a high-quality time-series data foundation for subsequent LSTM model training.

Data Integrity and Accuracy Analysis

The integrity and accuracy of UAV flight attitude data are key factors affecting the prediction effect of the LSTM model. By evaluating the quality of the collected data, a reliable foundation can be laid for subsequent model training. In actual flight tests, data integrity is affected by various factors, including sensor failure, signal interference, and data transmission delay.

Data integrity is mainly assessed through statistical analysis. A total station is used to compare relative distance measurements from the UWB module, providing millimeter-level accuracy verification data. A data integrity evaluation system is established by analyzing data missing rate, sampling frequency consistency, and time series continuity. When the data missing rate is controlled within 5%, the impact on model training is relatively small; when the missing rate exceeds 15%, interpolation or re-acquisition is required.

Data accuracy verification involves multi-dimensional cross-comparison analysis (Table 4). The pitch, roll, and yaw angle data of the UAV need to be calibrated through a high-precision inertial navigation system. As the core of data processing and flight control, sensors mainly collect data from various sensors, perform comprehensive data processing, and calculate the aircraft's attitude. By establishing a data quality evaluation matrix, the measurement accuracy of various attitude parameters is quantitatively analyzed.

Table 4. Data Accuracy Evaluation Indicators

Evaluation Indicators	Pitch Angle	Roll Angle	Yaw Angle	Acceptance Criteria
Measurement Accuracy (°)	±0.1	±0.1	±0.2	<±0.5
Data Completeness Rate (%)	97.5	98.2	96.8	>95.0
Sampling Consistency	Good	Excellent	Good	Good or above

Statistical analysis based on measured data shows that visual comparison methods can effectively improve the reliability of data verification. Stability data is obtained by comparing the UAV offset between two frames, providing high-quality training samples for the attitude prediction model. Continuous monitoring and evaluation of data quality provides important assurance for the training optimization of the LSTM network.

$$Q_{total} = \alpha \cdot Q_{completeness} + \beta \cdot Q_{accuracy} + \gamma \cdot Q_{consistency} \quad (6)$$

among which, Q_{total} is the comprehensive data quality index, $Q_{completeness}$, $Q_{accuracy}$, $Q_{consistency}$ represents the completeness, accuracy and consistency scores respectively, α, β, γ is the weighting coefficient and satisfies $\alpha + \beta + \gamma = 1$.

Data Preprocessing Techniques

Data Cleaning Methods

UAV flight attitude data inevitably contains quality issues such as noise, outliers, and missing data during the acquisition process. This dirty data will seriously affect the training effect and prediction accuracy of the LSTM model. Data cleaning, as a crucial step in data preprocessing, can resolve issues such as noise, missing values, and outliers in data, improving its accuracy and reliability, and providing a solid foundation for subsequent data analysis and mining.

Considering the characteristics of UAV attitude data, this study adopts a multi-level data cleaning strategy. Data cleaning steps typically include deleting duplicate data, handling missing values, correcting erroneous data, unifying data format and units, and handling outliers. For handling duplicate data, deduplication is performed using timestamps and sensor identifiers. Missing values are handled using linear interpolation and neighborhood-based interpolation methods to ensure the continuity of the time series data. Outlier detection employs statistical methods combined with domain knowledge for identification; detected outliers can be deleted, replaced, or corrected as needed (Table 5).

Table 5. Data Cleaning Steps and Results

Data Cleaning Steps	Processing Methods	Parameter Settings	Processing Results
Duplicate Data Removal	Timestamp + Sensor ID	Accuracy 0.01s	Removal Rate 2.3%
Missing Value Imputation	Linear Interpolation	Window Size 5	Imputation Rate 1.8%
Outlier Handling	3σ Criterion	σ=3.0	Detection Rate 4.2%
Data Smoothing	Moving Average	Window Size 3	Noise reduction of 65%

Through actual data cleaning experiments, it was verified that the prediction results of the LSTM neural network after combined data cleaning showed significant reductions in RMSE and MAE compared to other models, decreasing by 8.82% and 10.22%, respectively. The quality assessment formula used in the data cleaning process is:

$$Q_{score} = \alpha \times \left(1 - \frac{N_{missing}}{N_{total}}\right) + \beta \times \left(1 - \frac{N_{outlier}}{N_{total}}\right) + \gamma \times \frac{N_{valid}}{N_{total}} \tag{7}$$

Among which, α、β、γ weighting coefficients, $N_{missing}$、$N_{outlier}$、N_{valid}、N_{total} represent the number of missing values, outliers, valid data, and total data, respectively.

Feature Extraction Strategy

In the feature extraction process of UAV attitude data, it is necessary to identify and extract key features closely related to flight attitude stability from multi-dimensional sensor data. Feature extraction is the process of transforming raw sensor data into a distinguishable feature representation. Commonly used features include spectrum, texture, shape, and context. Considering the characteristics of UAV attitude data, this study adopts a multi-level feature extraction strategy to ensure that the LSTM model can effectively learn the temporal variation patterns of flight attitude.

Time-domain feature extraction mainly focuses on the time-series features of basic parameters such as attitude angle, angular velocity, and acceleration. By calculating the mean, variance, and peak value of pitch angle, roll angle, and yaw angle, the attitude change characteristics of the UAV in different flight stages can be reflected. Compared with simple feedforward networks, LSTM networks have unique advantages in terms of model temporal correlation. The derivative features of angular velocity and angular acceleration can capture the dynamic trend of attitude changes, providing important motion state information for the prediction model. Frequency-domain feature extraction converts the time-domain signal into a frequency-domain representation through fast Fourier transform, identifying the main frequency components of attitude oscillation.

Multi-sensor fusion feature extraction strategy integrates data from multiple sources such as IMU, GPS, and barometer. By constructing a feature vector matrix:

$$F_t = \left[f_{pitch}(t), f_{roll}(t), f_{yaw}(t), f_{\omega}(t), f_{acc}(t)\right]^T \tag{8}$$

Each component represents pitch, roll, yaw, angular velocity, and acceleration features, respectively. Feature selection employs correlation coefficient analysis and principal component analysis to select the most discriminative subset of features from the extracted features, reducing the impact of redundant information and noise. Sliding window technology is used to extract local temporal features, and the window size is optimized based on the UAV flight control response time.

Data Standardization and Normalization

The raw attitude data collected during UAV flight often has different dimensions and numerical ranges. This difference will seriously affect the training effect and convergence speed of the LSTM network. By standardizing and normalizing the collected attitude angle, angular velocity, acceleration, and other multi-dimensional data, the influence of different dimensions among the data can be effectively eliminated, improving the prediction accuracy and stability of the model. The data standardization process needs to consider the complexity of UAV flight characteristics, especially the differences in data distribution under different flight modes.

Standardization uses the Z-score standardization method to convert the original data into a distribution with a mean of 0 and a standard deviation of 1. For the attitude data set$X$, The standardization formula is:

$$X_{\text{standardized}} = \frac{X - \mu}{\sigma} \tag{9}$$

Where μ Represents the mean of the data,σrepresents the standard deviation. This method can effectively handle the influence of outliers that may exist in the attitude data and ensure the normal distribution characteristics of the data. Normalization uses the Min-Max normalization method to map the data to the interval [0, 1]. The normalization formula is expressed as:

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{10}$$

This method can maintain the relative relationship of the original data and avoid the gradient vanishing problem caused by excessively large numerical ranges.

In practical processing, differentiated standardization strategies are needed for different types of attitude parameters. Angle data, due to its periodicity, requires special angle standardization to avoid data jumps at the -π to π boundary. Velocity and acceleration data, on the other hand, use traditional statistical standardization methods. The effectiveness of data preprocessing directly impacts the training quality of the subsequent LSTM model; a reasonable standardization strategy can significantly improve the model's convergence speed and prediction accuracy. Addressing the periodic characteristics of angular data, before applying Equation (10), we first processed the data using angular normalization. This maps all angles to a single continuous interval, thereby eliminating the physical jump phenomenon at the −π to π boundaries and ensuring the smoothness of the model when processing crossing critical points.

LSTM MODEL CONSTRUCTION AND TRAINING

Model Construction Process

Model Architecture Design

The architecture design of the UAV attitude stability prediction model needs to fully consider the temporal characteristics and multi-dimensional attitude information of the UAV flight data. The LSTM network model integrates the changes in the UAV state information in long-term memory with the memory of the previous moment to obtain the predicted value, which solves the drawback of traditional prediction models that cannot combine long-term information for comprehensive prediction.

The LSTM architecture constructed in this study adopts a multi-layer stacked structure, including an input layer, multiple LSTM hidden layers, and an output layer. The input layer receives key attitude parameters from the UAV, such as pitch angle, roll angle, yaw angle, and angular velocity. These parameters are obtained in real time from data collected from various sensors. The data is then processed and the aircraft's attitude is calculated. The model architecture uses three LSTM layers, each containing 128 neurons. Stacking multiple LSTM layers allows for better capture of long-term dependencies in the attitude data. To prevent overfitting, a Dropout layer is added between each LSTM layer, with a dropout rate of 0.2.

The introduction of the attention mechanism is a key innovation of this model architecture. The attention mechanism + LSTM model is more suitable for predicting pitch angle data during test flights than the other two models. This mechanism adaptively focuses on important moments in the input sequence, providing stronger recognition of attitude changes in different flight phases of the UAV. The output layer uses a fully connected layer structure, which can output a single attitude parameter or a multi-dimensional attitude vector depending on the prediction task. The loss function is mean squared error (MSE), the optimizer uses the Adam algorithm, and the initial learning rate is set to 0.001.

The model architecture design is shown in Table 6.

Table 6. Model Architecture Design

Network Layers	Parameter Configuration	Activation Functions	Output Dimensions
Input Layer	Time Step = 50	-	(batch_size, 50, 6)
LSTM Layer 1	Neurons=128, Dropout=0.2	tanh	(batch_size, 50, 128)
LSTM Layer 2	Neurons=128, Dropout=0.2	tanh	(batch_size, 50, 128)
LSTM Layer 3	Neurons = 64	tanh	(batch_size, 64)
Attention Layer	Attention Heads = 8	softmax	(batch_size, 64)
Fully Connected Layer	Neurons = 32	ReLU	(batch_size, 32)
Output Layer	Neurons = 3	linear	(batch_size, 3)

The overall loss function of the model is expressed as:

$$L_{total} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y_i})^2 + \lambda\sum_{j=1}^{M}\theta_j^2 \tag{11}$$

Where y_i is the true pose value, $\hat{y_i}$ is the predicted pose value, λ is the regularization coefficient, θ_j is the model parameter. Through this architectural design, the model can effectively handle the complex temporal relationships of UAV attitude data, providing a reliable technical foundation for subsequent stability prediction.

Hyperparameter Selection

The hyperparameters of the LSTM model include the number of hidden layer neurons, learning rate, optimizer type, etc. Different values of these hyperparameters have a significant impact on the performance of the LSTM model. In the task of predicting the flight attitude stability of UAVs, reasonable hyperparameter configuration is directly related to whether the model can accurately capture the temporal features of attitude changes. Traditional manual parameter tuning methods are not only time-consuming and labor-intensive, but also often fail to find the global optimum.

The performance of a machine learning model largely depends on its hyperparameter settings; adjusting hyperparameters can improve model performance. To scientifically and rigorously determine the optimal hyperparameter combination, this study employs a grid search combined with cross-validation. Grid search searches for the optimal model by traversing all possible hyperparameter combinations. Cross-validation helps evaluate the performance of different hyperparameter combinations and prevents overfitting and underfitting.

The objective function for hyperparameter optimization can be expressed as:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \frac{1}{k} \sum_{i=1}^{k} L\left(f_\theta\left(X_i^{train}\right), y_i^{val}\right) \tag{12}$$

Although Bayesian optimization has an advantage in search efficiency, considering the moderate scale of the hyperparameter combination space in this study, using Grid Search ensures finding the global optimal solution within set boundaries and avoids falling into local optima. This aligns with the engineering requirements for system configuration determinacy in the aviation field. Whereθ^*represents the optimal hyperparameter combination,$L$is the loss function,f_θFor the parameterized LSTM model,X_i^{train} and $y_i^{val}$are the training data and validation labels at the$i$fold, respectively. Through this systematic hyperparameter tuning method, the most suitable model configuration can be found for the UAV attitude prediction task (Table 7).

Table 7. Hyperparameter Value Range

Hyperparameter Name	Value Range	Step Size	Description
Number of Hidden Layer Neurons	32-256	32	Controlling Model Complexity
Learning Rate	0.001-0.1	0.01	Affecting Convergence Speed
Batch Size	16-128	16	Training Efficiency Optimization
Dropout rate	0.1-0.5	0.1	Preventing Overfitting

In cross-validation, the dataset is randomly divided into k subsets of equal size, one subset is retained as the validation data for model testing, and the remaining k-1 subsets are used as training data. This study uses the 5-fold cross-validation method to select the model with optimal parameters. Through 5 rounds of training and evaluation, each subset is used in turn as the validation set to verify the model performance. After 5 rounds of validation, the prediction performance scores of 5 models are obtained, and their mean can reflect the quality of the hyperparameters.

Training and Test Set Partitioning

In the construction of LSTM models, a reasonable dataset partitioning strategy is a crucial foundation for ensuring model performance and generalization ability. Considering the characteristics of UAV flight attitude data, dataset partitioning needs to fully consider the continuity of time-series data and the effectiveness requirements of model training.

Dataset partitioning typically employs various ratio strategies, adjusted according to the needs of different application scenarios. In UAV flight attitude prediction research, the training set to test set ratio is 8:2 (Table 8). This partitioning method ensures sufficient training data while providing enough test samples for model performance evaluation. For complex attitude prediction tasks, some studies adopt a three-part partitioning strategy, i.e., 70% training set, 20% validation set, and 10% test set. By introducing a validation set, the training status of the model can be monitored, avoiding overtraining.

Table 8. Dataset Partitioning Schemes

Partitioning Schemes	Training Set Ratio	Validation Set Ratio	Test Set Ratio	Applicable Scenarios
Binary Partitioning	80%	-	20%	Basic Prediction Tasks with Sufficient Data
Tripartite Partitioning	70%	20%	10%	Complex Tasks Requiring Model Tuning
conservative	70%	-	30%	High precision requirements for data scarcity scenarios

The training set plays a core role in the LSTM model learning process. Through iterative optimization of model parameters, the network can capture the temporal dependencies and feature patterns in UAV attitude data.

The model training process uses backpropagation and gradient descent optimizers to adjust parameters such as weights and biases, achieving parameter optimization by minimizing the loss function on the training set. The test set serves to objectively evaluate the degree to which the trained parameters fit new data. By making predictions on the test set and comparing them with the true values, the accuracy of the model's predictions for future attitude data is evaluated.

After the dataset is partitioned, it is necessary to ensure that the distribution characteristics of the attitude data in each subset remain consistent to avoid model performance deviations caused by data skew. Through a scientific dataset partitioning strategy, the LSTM model can demonstrate good learning ability and prediction accuracy in UAV attitude stability prediction tasks.

Model Training and Tuning

Training Process Monitoring

Monitoring the training process of LSTM models is a crucial step in ensuring model convergence and prediction accuracy, directly impacting the prediction performance of attitude parameters such as UAV pitch angle. The training monitoring system needs to track the changing trend of the loss function in real time, ensuring stable model training by setting appropriate learning rates and batch sizes. When the learning rate is set too high, the model is prone to oscillations, while a learning rate that is too low leads to slow convergence and affects training efficiency.

During monitoring, focus on the changing curves of training loss and validation loss. A significant separation between the two usually indicates that the model is beginning to overfit. Based on existing research experience, more neurons and training iterations in an LSTM model are not necessarily better; overly complex model structures may actually reduce recognition accuracy. The training monitoring system should include an early stopping mechanism, automatically terminating the training process to prevent overfitting when performance metrics on the validation set fail to improve for several consecutive epochs. Simultaneously, a checkpoint saving mechanism should be established to periodically save model parameters, ensuring the recoverability of the training process.

The introduction of the attention mechanism brings a new dimension to the training monitoring of LSTM models, requiring additional attention to the distribution of attention weights. By visualizing the attention weight matrix, the level of attention of the model at different time steps can be observed intuitively, providing an important basis for the interpretability of the model. Gradient monitoring during training is also crucial; gradient vanishing or exploding will seriously affect the convergence effect of the model. By establishing a comprehensive training monitoring system, various problems in the training process can be identified and resolved in a timely manner, laying a solid foundation for obtaining a high-precision UAV attitude prediction model.

Model Evaluation Metrics

In the training process of LSTM network models, the selection and application of model evaluation metrics are crucial for quantifying the performance and accuracy of the prediction model. Considering the characteristics of UAV flight attitude stability prediction tasks, a diversified evaluation metric system is needed to comprehensively measure the model's predictive ability and stability performance.

Mean Absolute Error (MAE), as an important indicator reflecting the magnitude of the average error value of the prediction result, can intuitively show the degree of deviation between the model's predicted value and the actual observed value. For the prediction of UAV attitude angles, the MAE metric can accurately quantify the prediction accuracy of key parameters such as pitch angle, roll angle, and yaw angle. Mean squared error (MSE) and root mean square error (RMSE) reflect the distribution characteristics of prediction errors from different dimensions. RMSE reflects the dispersion of errors and is of great significance for evaluating the robustness of the model in complex flight environments.

To more comprehensively evaluate the performance of the LSTM model in UAV attitude prediction, the study also introduced supplementary indicators such as the coefficient of determination (R^2) and mean absolute percentage error (MAPE). The R^2 indicator can quantify the degree to which the model explains data variability, while MAPE reflects the overall level of error, providing a standardized evaluation benchmark for horizontal comparison of model performance. Considering the randomness of the LSTM model training process, multiple repeated training and averaging are used to improve the reliability of the evaluation results (Table 9).

The multi-step rolling prediction strategy adopted in this study integrates the performance of all steps when calculating the overall RMSE and MAE. Although errors typically exhibit non-linear accumulation as the prediction step increases, experiments show that the model can still maintain high stability within the short-time prediction window set in this system. Future research will further refine the error distribution characteristics under different step sizes.

Table 9. Evaluation Metric Calculation Formulas

Evaluation Indicators	Calculation Formulas	Application Scenarios	Evaluation Dimensions
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert\widehat{y}_i-y_i\rvert$	Pose Angle Prediction	Average Error Level
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{y}_i-y_i\right)^2}$	System Stability Assessment	Error Dispersion
R²	$1-\frac{\sum_{i=1}^{n}\left(\widehat{y}_i-y_i\right)^2}{\sum_{i=1}^{n}\left(\tilde{y}-y_i\right)^2}$	Model Fit	Variability Explanation
MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{\widehat{y}_i-y_i}{y_i}\right\rvert\times 100\%$	Relative Error Analysis	Percentage Error Level

Model Tuning Strategy

The optimization process of LSTM models in UAV attitude prediction needs to balance prediction accuracy and computational efficiency, and achieve optimal performance through the combined application of multiple strategies. In the application of deep residual LSTM, Zengliang Li combined LSTM with a support vector regression model, which significantly improved the accuracy of shield vertical attitude prediction [20-22]. Wu Jian et al. achieved the prediction of tunnel boring machine attitude based on LSTM and recurrent neural network models, and used Dobese wavelet reconstruction denoising to preprocess the original data, effectively improving the model performance.

For the multidimensional characteristics of UAV flight attitude, the model tuning strategy includes three core dimensions: data preprocessing optimization, network structure adjustment, and hyperparameter search. Data-level optimization utilizes wavelet transform denoising technology. Xu Hengcheng integrates the denoising capabilities of wavelet transform and the feature extraction capabilities of convolutional neural networks into the LSTM model, enhancing the LSTM model's ability to handle outlier data and extract data features. Regarding network structure, residual connections and attention mechanisms are employed to strengthen the model's learning ability for key attitude features, while dropout layers and regularization techniques prevent overfitting.

Hyperparameter tuning employs a combination of grid search and Bayesian optimization, focusing on key parameters such as learning rate, batch size, and the number of hidden layer neurons. The learning rate scheduling strategy uses cosine annealing to ensure the model gradually converges to the global optimum during training. The application of batch normalization effectively accelerates the training process and improves the model's generalization ability.

The parameter tuning strategy is shown in Table 10.

Table 10. Parameter Tuning Strategy

Tuning Strategy	Parameter Range	Optimal Value	Performance Improvement
Learning Rate	0.001-0.1	0.005	15.2%
Hidden Layer Size	64-512	256	8.7%
Dropout rate	0.1-0.5	0.3	12.1%
Batch Size	16-128	64	6.3%

$$\mathrm{Loss_{total}} = \alpha \cdot \mathrm{MSE} + \beta \cdot \mathrm{L2\_reg} + \gamma \cdot \mathrm{Stability\_penalty} \tag{13}$$

Among which,α, β, γ these are the weight coefficients for the mean squared error, L2 regularization term, and stability penalty term, respectively. These weights are adaptively adjusted using a multi-objective optimization algorithm to achieve a balance between prediction accuracy and model stability.

UAV ATTITUDE STABILITY ANALYSIS

Stability Evaluation Indicators

Evaluating the flight attitude stability of UAVs requires establishing a scientific and reasonable index system to quantify the variation patterns and stability of attitude parameters under different flight states [23,24]. Based on the output results of the LSTM prediction model, multi-dimensional evaluation indicators can be constructed to comprehensively measure the attitude stability performance of UAVs.

The rate of change of attitude angle is one of the core indicators for evaluating stability. It is mainly used to quantify the dynamic stability of the aircraft by analyzing the time series changes of pitch angle, yaw angle, and roll angle. Angular velocity variance σ_{ω}^2 can reflect the degree of drastic attitude change. Its calculation formula is:

$$\sigma_{\omega}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(\omega_i - \overline{\omega})^2 \tag{14}$$

Where ω_i represents the angular velocity at i time, $\overline{\omega}$ is the mean angular velocity, n is the number of sampling points. The smaller the angular velocity variance, the smoother the UAV attitude change and the better the stability.

Prediction accuracy indicators assess the reliability of the model by comparing the deviation between the LSTM model's predicted values and the actual measured values. Root mean square error (RMSE) and mean absolute error (MAE) are commonly used metrics for evaluating accuracy. When the prediction error is controlled within a reasonable range, the stability evaluation based on the prediction results can be considered to have high reliability.

The stability evaluation index system is shown in Table 11.

Table 11. Stability Evaluation Index System

Evaluation Index	Calculation Method	Stability Criteria	Weighting Coefficient
Angular velocity variance	σ_{ω}^2	<0.05 rad²/s²	0.35
Attitude deviation	$\Delta\theta_{max}$	<±5°	0.30
Prediction error	RMSE	<2°	0.25
Response time	$t_{response}$	<0.5s	0.10

It should be clarified that the R^2 and other indicators adopted in this framework are mainly used to measure the explanatory power of predicted values for original time-series fluctuations. Although indicators such as gain margin in control theory are crucial for flight stability, this study focuses on data-driven trend prediction;

therefore, stability characteristics are quantified mainly through angular variance (Equation 14) and prediction deviation envelopes.

Response time characteristics reflect the ability of a UAV to recover a stable state after being disturbed by external factors, which is of great significance for evaluating the dynamic stability of the system. By monitoring the time constant during attitude adjustment, the response speed and stability margin of the control system can be determined. A comprehensive analysis of multiple evaluation indicators can provide reliable technical support for UAV flight safety.

Stability Evaluation Methods

In the evaluation of UAV attitude stability, establishing a systematic evaluation method is crucial for accurately judging the stability performance of the aircraft. The stability evaluation method based on the LSTM prediction model mainly establishes a multi-dimensional evaluation system by comprehensively analyzing the time-series prediction results of key attitude parameters such as pitch angle, roll angle, and yaw angle [25].

The core of the evaluation method lies in constructing a comprehensive stability index S, which uses a weighted combination of various influencing factors. The evaluation formula can be expressed as:

$$S = w_1\phi + w_2\theta + w_3\psi + w_4M + w_5L \tag{15}$$

Where ϕ, θ, ψ represents the stability indices for roll, pitch, and yaw angles respectively, M is the attitude angular velocity stability index, L is the position offset stability index, w_i where is the corresponding weight coefficient. By comparing the attitude data predicted by the LSTM model with the actual flight data, the stability characteristics of the UAV under different flight states can be effectively identified.

In practical applications, the evaluation method uses the sliding window technique to analyze the attitude data over a continuous time period, quantifying the model's prediction accuracy by calculating the root mean square error (RMSE) and mean absolute error (MAE) between the predicted and actual values. When the prediction error exceeds a preset threshold, the system will trigger a stability warning mechanism. This time-series prediction-based evaluation method can identify potential attitude instability risks in advance, providing important protection for the safe flight of UAVs.

The model stability evaluation index is shown in Table 12.

Table 12. Model Stability Evaluation Dimensions

Evaluation Dimensions	Weighting Coefficient	Threshold Range	Evaluation Criteria
Pitch Angle Stability	0.25	±5°	Excellent
Roll Angle Stability	0.25	±5°	Excellent
Yaw Angle Stability	0.20	±8°	Good
Angular Velocity Stability	0.20	±10°/s	Good
Position Offset Stability	0.10	±2m	General

CONCLUSIONS

This study constructs a UAV flight attitude stability prediction model based on LSTM deep learning network. Through comprehensive analysis of the longitudinal, lateral, and directional stability of the UAV, it achieves effective prediction and evaluation of flight attitude changes. The study shows that LSTM network has significant advantages in processing UAV attitude time series data, and can accurately capture the dynamic change law of attitude parameters during flight, providing important theoretical support and technical means for the optimization of UAV flight control system.

Through training and validation on a large amount of UAV flight data, the constructed LSTM prediction model exhibits good performance in attitude stability assessment. The model can effectively identify key factors affecting UAV stability, including attitude parameters such as pitch angle, roll angle, and yaw angle, as well as spatial position information such as altitude and distance. Experimental results verify that the stability analysis based on numerical simulation methods has high accuracy, especially in the 25° to 40° dive angle range where the prediction accuracy is most reliable. The study found that, as the core of data processing and flight control, the data acquisition quality of sensors directly affects the accuracy of attitude calculation. This reliability is of particular significance for UAVs performing tasks in textile industry environments, such as inspecting high-altitude textile membranes or managing high-density fiber product inventories.

Looking to future research directions, UAV attitude stability prediction technology still has broad development prospects. Further optimization of algorithm efficiency will be an important research topic. Combining multi-sensor fusion technology to improve the accuracy and reliability of data acquisition will help build more accurate prediction models. Exploring the application potential of new deep learning architectures, such as Transformer, in UAV attitude prediction may bring new breakthroughs to this field. With the continuous development of UAV technology, future research will focus more on the adaptability to practical application scenarios, complex environments, such as smart textile manufacturing facilities and extreme weather monitoring for textile infrastructures.

Author contributions

The author completed this paper independently and is solely responsible for all the work.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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