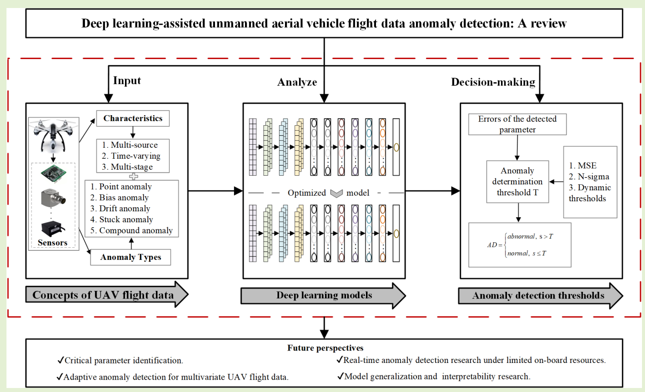
Deep Learning-Assisted Unmanned Aerial Vehicle Flight Data Anomaly Detection: A Review

Lei Yang, Shaobo Li, Yizong Zhang, Caichao Zhu, and Zihao Liao

***Abstract*—Flight data anomaly detection is crucial for ensuring the flight safety of unmanned aerial vehicles (UAVs). By monitoring and analyzing flight data, anomalies can be detected in time to avoid potential risks. Deep learning can automatically extract complex patterns and features from data and has been widely used in UAV flight data anomaly detection in recent years. Given the lack of a comprehensive survey of research related to deep learning in UAV flight data anomaly detection, this article conducts a systematic and in-depth literature review. First, the basic concepts of UAV flight data are briefly introduced, followed by an analysis and summary of the applications of deep learning methods based on prediction and reconstruction in UAV flight data anomaly detection. Emphasis is placed on the research progress of deep learning methods based on recurrent neural network (RNN), convolutional neural network (CNN), auto-encoder (AE), and variational AE (VAE) for UAV flight data anomaly detection. Second, an in-depth analysis of the threshold calculation methods utilized in existing research is conducted and the advantages and limitations of these thresholds in practical applications are discussed. Finally, some insightful research directions are given based on the shortcomings of existing research. This work aims to provide a reference and insight for future research, inspire further studies, and jointly promote the development of this promising field.**



***Index Terms*—Anomaly detection, deep learning, flight data, unmanned aerial vehicle (UAV).**

I. Introduction

WITH the advancing technology and expanding market scale of unmanned aerial vehicles (UAVs), their applications in forest health monitoring [1], marine monitoring [2], agriculture [3], and search and rescue [4] are becoming more and more widespread and important. However, UAVs may face various environmental and technical challenges, which may lead to anomalies or accidents involving UAVs. Therefore, although UAVs provide convenience for performing various tasks [5], their frequent accidents in recent years have caused huge economic losses to relevant countries and enterprises [6], [7]. In this context, the demands for the safety and reliability of UAVs are increasing. However, as closed-loop control systems, UAVs lack real-time decision-making by pilots, presenting significant challenges in ensuring their safe and reliable flight. Thus, many studies on UAVs prognostics and health management (PHM) [8], [9], [10], [11], [12], [13], [14], [15], [16] have emerged to address these challenges. For example, redundant system design can be used to improve the reliability and fault tolerance of UAVs [17]. This ensures that even if certain components or sensors are abnormal or failure, the system can continue to operate or maintain functionality by switching to alternate components. With the rapid development of artificial intelligence and big data technology, the potential value of data has been further explored. Flight data are an important indicator to assess the performance of UAV flight status. Therefore, detecting possible anomalies in flight data is important to ensure the safety of UAVs [18], [19].

Anomaly detection refers to identifying potential anomalies by analyzing data or behavioral patterns that significantly differ from the normal state [20]. It focuses on discovering

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data points or patterns that deviate significantly from normal behavior. In contrast, fault detection aims to identify and detect faults within a system or device, typically manifested as abnormalities in its operational state [21]. Thus, fault detection can be considered a part of anomaly detection and is included in the broader topic of anomaly detection in flight data for analysis and discussion in this article. Anomaly or fault detection requires establishing a model of the normal operating state and subsequently detecting anomalies or faults by comparing deviations against predefined thresholds. Traditional machine learning-based methods like k-means [22], [23], [24], [25], k-nearest neighbors (KNNs) [26], [27], [28], [29], kernel principal component analysis (KPCA) [30], [31], [32], [33], support vector machine (SVM) [29], [33], [34], [35], [36], [37], [38], [39], Bayesian network (BN) [40], [41], decision tree (DT) [29], [42], [43], Kalman filter (KF) [7], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], random forest (RF) [54], [55], as well as statistics-based methods like Least square [56], [57], [58], [59] and Mahalanobis distance (MD) [60], which have been widely used for UAV flight data anomaly or fault detection. However, these methods may demonstrate limited flexibility and adaptability when handling complex flight data due to the complex meteorological conditions and diverse task requirements in UAV operational environments, coupled with UAV systems' nonlinearity and high dynamics. Driven by this demand, significant progress has been made in UAV flight data anomaly detection with the assistance of deep learning in recent years. Deep learning reduces the reliance on manual feature engineering through end-to-end learning [61], thus providing a more powerful tool to address the complexities of dynamic flight environments of UAVs. For example, deep learning methods such as convolutional neural network (CNN) [62] and long short-term memory (LSTM) [63], [64] network can automatically learn data patterns, which allows more flexibility in detecting complex anomaly patterns in flight data.

Several review studies have reported on the research progress of UAV flight data anomaly or fault detection. Puchalski and Giernacki [21] systematically surveyed papers on UAV fault detection included in the Web of Science and Google Scholar between January 2016 and August 2022. They focused on the research progress of data- and model-based and hybrid data- and model-based approaches, and analyzed and summarized their advantages and disadvantages in detail. Yang et al. [6] discussed and summarized the knowledge-based, model-based, and data-driven anomaly detection methods for UAV flight data and their applications and presented related datasets and UAV simulation software. On this basis, they pointed out the future directions that were worth researching in model interpretability, data-driven algorithms, hybrid models, and transfer learning-based and UAV cluster anomaly detection. However, these reviews lack a detailed discussion on the application of deep learning methods for flight data anomaly detection of UAVs. Particularly, in recent years, data-driven methods based on deep learning have gradually emerged as mainstream approaches. However, there remains a lack of comprehensive summary and evaluation of the application of deep learning in this area.

To fill this gap, we conduct a systematic review aiming at deeply analyzing the research progress of deep learning-based methods for UAV flight data anomaly detection. This study specifically addresses problems stemming from anomalies in flight data. It does not consider related issues such as power system and structural failures, as well as the influence of flight dynamics variations and external environmental disturbances on the data. The main contributions of this article compared to previous studies are described as follows.

1) We provide a comprehensive overview of deep learning-assisted anomaly detection methods for UAV flight data. So far, there is almost no comprehensive review literature in the field dedicated to deep learning methods. Especially with the rapid development of deep learning technology, it is necessary to deeply investigate its latest research progress in UAV flight data anomaly detection. Therefore, we provide sufficient details about the deep learning-assisted anomaly detection methods for UAV flight data.
2) We analyze and summarize commonly used anomaly determination threshold calculation methods in order to gain insight into the field, especially the description of threshold aspect content not covered in the existing review literature.
3) We determine some future research directions for UAV flight data anomaly detection.

The rest of this article is organized as follows. Section II describes the research methodology. Section III introduces the basic concepts of UAV flight data. Section IV provides an in-depth analysis of deep learning-assisted UAV flight data anomaly detection methods. The commonly used anomaly detection determination thresholds are highlighted in Section V. Section VI gives the future directions. Section VII summarizes this work.

II. Research Methodology

A. Keywords and Databases

To comprehensively consider the relevant literature reported in the field of UAV flight data anomaly detection, a series of keywords that include UAV, drone, flight data, fault detection, and anomaly detection were combined. These keywords were then extensively searched in several reputable academic databases, including IEEE EXPLORE, Google Scholar, and Web of Science. This search strategy was designed to ensure that we could cover a broad and related field. The specific timeframe of the search was from 2013 to 2023 to ensure a more comprehensive collection of literature associated with anomaly detection in UAV flight data.

B. Statistics and Analysis of Literature

Based on Section II-A, the collected related literature was systematically counted and analyzed, as shown in Fig. 1. From 2013 to 2023, a total of 108 papers were screened, as shown in Fig. 1(a), among which the number of papers for 2022 and 2023 stands out with 16 and 18 papers, respectively. These papers were categorized in detail based on their publication channels and formats, including conference papers, journal papers, and preprints, numbering 45, 61, and 1, respectively, as shown in Fig. 1(b). These papers are further divided into deep learning-, traditional machine learning-, statistics-, reinforcement learning-based, and other methods. Specifically,

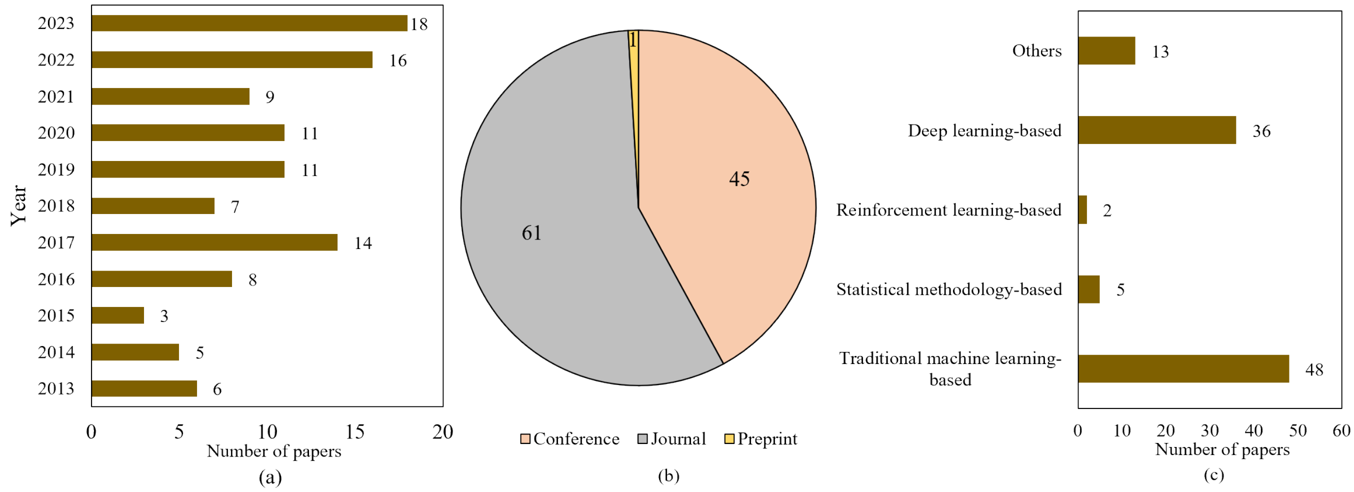

Fig. 1. Statistics of field-related literature (a) published papers per year from 2013 to 2023, (b) published article types, and (c) methods used in the papers.

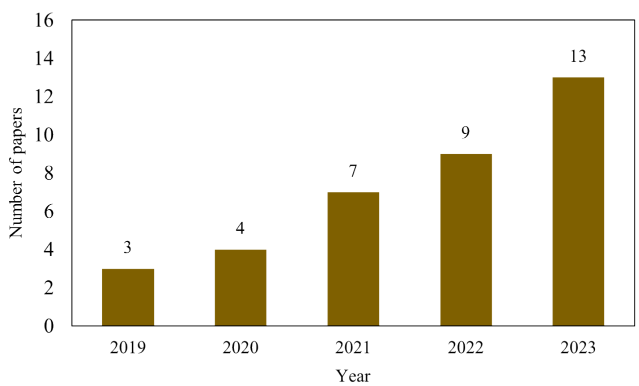

Fig. 2. Distribution of literature based on deep learning methods.

48 papers used traditional machine learning-based methods, five papers used statistics-based methods, two papers used reinforcement learning-based methods, 36 papers used deep learning-based methods, and 13 papers used other methods or review papers, as shown in Fig. 1(c).

C. Selection Standard

According to the collected literature as described in Section II-B, we retained the articles that only employ deep learning. As shown in Fig. 2, deep learning-based methods are mainly concentrated from 2019 to the present, with an increasing trend year by year. Although some of the literature titles or abstracts involve anomaly or fault detection, a closer reading reveals that they focus more on fault classification [65], [66], [67], [68]. Given that this article is primarily concerned with binary classification, i.e., normal or abnormal, the choice is to exclude this part of the literature. It was also noted that some journal papers were extended versions of conference papers. For example, [69] is a journal paper based on the conference [70]. Therefore, these more informative journal papers are the main objects discussed in this article. After a series of analyses and selection, 25 papers were finally included in the discussion of this article.

III. Basic Concepts of UAV Flight Data

Flight data is a series of parameters related to the flight and operational status of aircraft. Considerable studies have been focusing on analyzing and modeling flight data from UAVs [71], [72], commercial aircraft [73], [74], [75], [76], and helicopters [77], [78] to develop health monitoring methods. In this case, flight data serves as a crucial carrier of information, and it is necessary to understand the detailed information associated with flight data. Therefore, this section provides a more comprehensive analysis and summary of UAV flight data characteristics and common anomaly types.

A. Characteristics of UAV Flight Data

UAV flight data include flight parameters such as attitude, acceleration, pitch, roll, longitude, and latitude of UAVs. These parameters are collected by sensors equipped with UAVs and cover flight data in different periods and flight stages, as shown in Fig. 3. Therefore, UAV flight data have the characteristics of multisource, time-varying, and multistage.

1) Multisource: UAV flight data are typically collected from multiple sensors, including Global Positioning Systems (GPS), gyroscopes, accelerometers, and gaussmeter sensors. Each sensor records one or more flight parameters. This multisource makes UAV flight data high dimensional and complex spatial-temporal correlation [79].

2) Time-Varying: Flight data belong to typical time-sequence data and is time-varying. This means that UAVs will constantly change their flight data, such as position, speed, and attitude. These flight data will be generated continuously as data streams and contain UAV flight data at each moment.

3) Multistage: The flight process of UAVs involves several flight stages, such as taxi, takeoff, cruise, descent, and landing [80]. Each flight stage is characterized differently. For example, during the takeoff stage, more attention may be paid to the acceleration and altitude changes. The cruise stage may be more concerned with speed and flight path.

B. Common Anomaly Types of UAV Flight Data

There seems no consensus on the definition of the outlier so far [81]. The more classical view is that outliers are observed

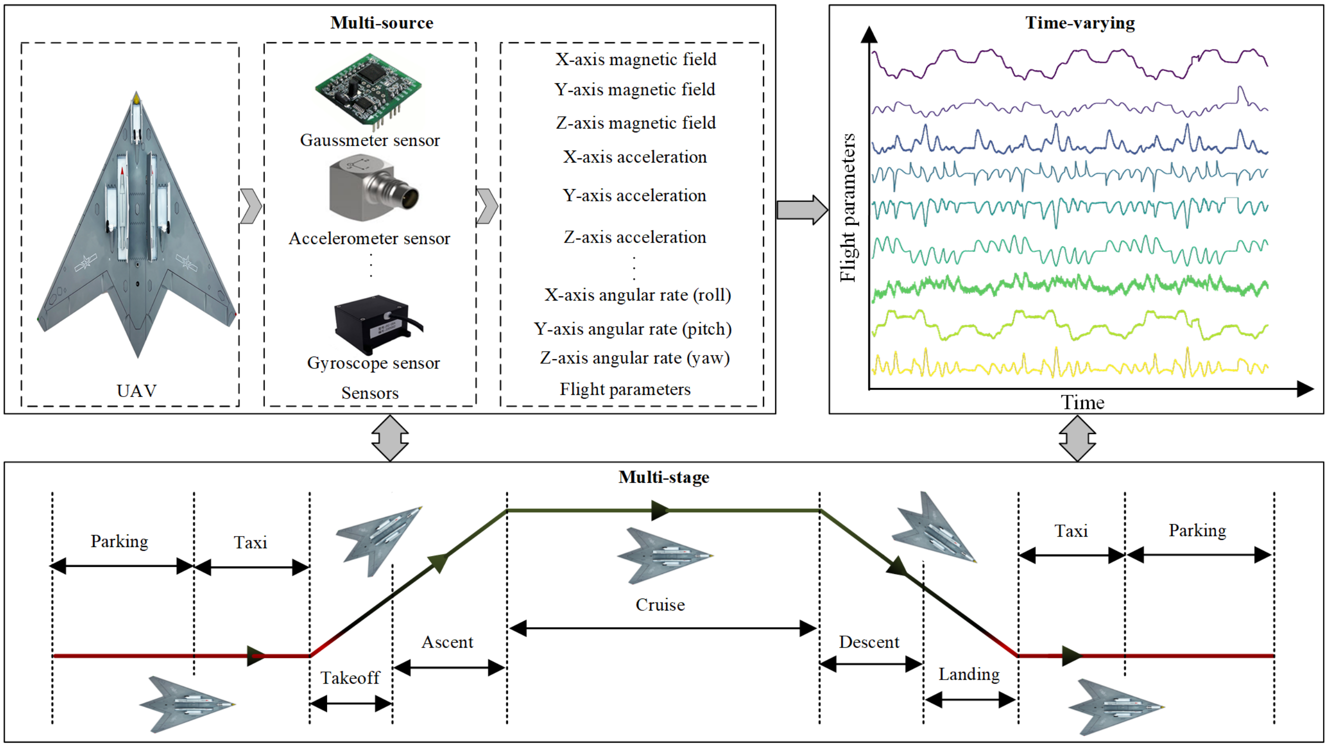

Fig. 3. Multisource, time-varying, and multistage characteristics of UAV flight data.

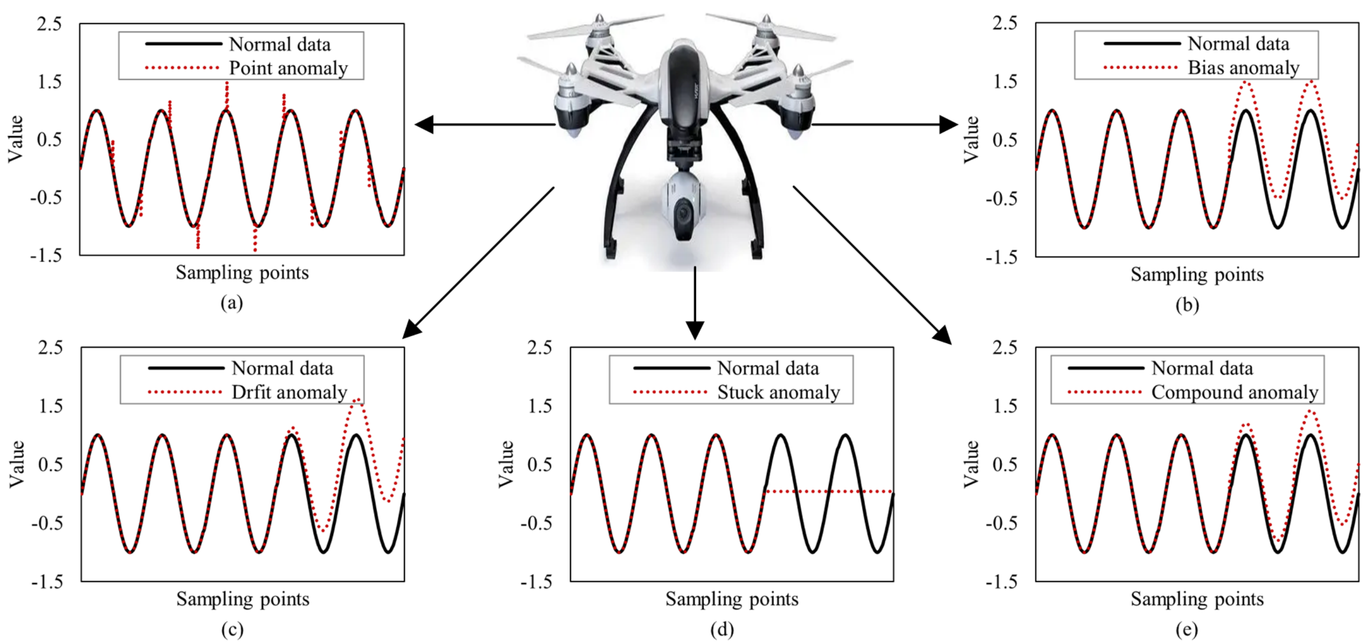

Fig. 4. Common types of UAV flight data (a) point, (b) bias, (c) drift, (d) stuck, and (e) compound anomalies.

results that are not consistent with expected behavior [20]. Considering the temporal characteristics of UAV flight data, its anomaly types can be broadly categorized into point, contextual, and collective anomalies [82]. In this context, it can be further divided into point, bias, drift, stuck, and compound anomalies based on existing studies [63], [71], [79]. Fig. 4 briefly illustrates the behavior of each anomaly type.

1) Point Anomaly: Point anomaly refers to the sudden deviation of UAV flight data from the expected value at a certain moment, showing instantaneous abnormal changes, as shown in Fig. 4(a). For example, when the GPS satellite search conditions are poor, the GPS sensor output has a large error at one point and then the output is correct [83]. Factors such as environmental noise, measurement system errors, and operational errors can also cause flight data to exhibit multiple discrete outliers [26]. Its expression is defined as follows:

$$y_{\text{point}}(t) = y(t) + \alpha \tag{1}$$

where $y_{\text{point}}(t)$ and $y(t)$ are the point anomaly and normal data, respectively, t is a discontinuous time point, and α is a constant or a variable constant.

2) Bias Anomaly: Bias anomaly refers to UAV flight data that continuously deviates from the expected value with a constant deviation value over a period, as shown in Fig. 4(b). Factors such as sensor, actuator, and control surface faults may cause bias anomalies in flight data [59], [83], [84]. For example, temperature change or vibration disturbance causes bias current or bias voltage [83]. A bias difference between the actual and commanded deflections reflected on the control surface due to slipping servo actuator gears or bent control linkages [84]. Its expression is defined as follows:

$$y_{\text{bias}}(t) = y(t) + \beta \tag{2}$$

where $y_{\text{bias}}(t)$ is the bias anomaly data and β is a fixed bias constant.

3) Drift Anomaly: Drift anomaly refers to the UAV's flight data gradually deviating from the expected value within a certain period of time during the flight process, showing a continuous increasing or decreasing trend, as shown in Fig. 4(c). Unlike bias anomaly, drift anomaly changes gradually over time. Factors contributing to drift anomalies may include sensor or actuator faults such as temperature change, uncalibrated sensor, change in elevator leveling, servo power reduction, and main rotor power reduction [59], [83], [85]. Its expression is defined as follows:

$$y_{\text{drift}}(t) = y(t) + \eta(t) \tag{3}$$

where $y_{\text{drift}}(t)$ is the drift anomaly data and $\eta(t)$ is a function of t. In some studies, $\eta(t)$ can also be expressed as $\eta(t) = k \times t$, where k is the drift rate [63], [86].

4) Stuck Anomaly: Stuck anomaly means that the UAV flight data suddenly stops changing at a certain moment and stays at a fixed value that no longer fluctuates, as shown in Fig. 4(d). For example, a stuck rudder or engine failure will result in a constant output [59]. Servo power and main rotor power decline will cause the actuator to stay in a fixed position whatever the input value is [87]. Factors such as the broken control linkage and broken servo gears can lead to the control surfaces being stuck in a certain position [84]. Communication link and power interruption anomalies can also cause the sensor to output a zero or constant value at a certain point [83]. Its expression is defined as follows:

$$y_{\text{stuck}}(t) = \varepsilon \tag{4}$$

where $y_{\text{stuck}}(t)$ is the stuck anomaly data and ε is a constant.

5) Compound Anomaly: Compound anomaly is a phenomenon in which multiple anomalies, such as simultaneous bias, drift, and point anomalies, occur in UAV flight data at a given period of time, as shown in Fig. 4(e). Factors contributing to the anomaly may include the combined effects of various factors like temperature change, sensor and actuator faults, power interruptions, environmental noise, etc., as mentioned above, resulting in complex anomalies in the UAV during flight. Its expression is defined as follows:

$$y_{\text{compound}}(t) = y(t) + \gamma(t) \tag{5}$$

where $y_{\text{compound}}(t)$ is the compound anomaly data and $\gamma(t)$ is a function of t. It contains several terms and the form of each term corresponding to time t may not be identical.

It needs to be emphasized that while different types of UAVs, such as fixed-wing and multirotor UAVs, may exhibit similar anomalies in flight data, the specific components associated with these anomalies may differ significantly, especially the differences in control surfaces and flight behaviors. Some anomalies are unique to fixed-wing UAVs such as elevator and aileron control failures. Anomalies such as propeller damage are unique to multirotor UAVs.

IV. Deep Learning-Assisted Anomaly Detection for UAV Flight Data

As seen from Section II, researchers have been actively exploring various deep learning-based methods since 2019 for UAV flight data anomaly detection. Based on existing studies, deep learning-based approaches can be divided into prediction- and reconstruction-based methods [63], [79], [88], [89]. Prediction-based approaches detect anomalies by predicting future data and comparing the residuals between predicted and actual values with a given threshold, while reconstruction-based methods detect anomalies by reconstructing existing data and comparing reconstruction errors with a given threshold. The former focuses on the prediction error of future data, while the latter focuses on the reconstruction error of existing data. Based on deep learning algorithms, prediction-based methods can be categorized into recurrent neural network (RNN)- and CNN-based approaches [62], [79], [90], [91], and reconstruction-based methods can be divided into auto-encoder (AE)- and variational AE (VAE)-based approaches [88], [89], [92], [93]. This section focuses on the research progress of these methods in UAV flight data anomaly detection based on the introduction of the problem definition.

A. Problem Definition

The aim of UAV flight data anomaly detection is to identify data points that deviate from normal flight patterns. After model testing, each test data point x is assigned a score s. The larger the value of s, the more likely that x is an anomaly. The specific determination is made by comparing s to a given threshold T. If $s > T$, then x is abnormal, and vice versa.

B. Prediction-Based Anomaly Detection Methods

Prediction-based anomaly detection methods are used to identify anomalies in data by building prediction models [94]. These methods assume that the farther the data points are from the normal data distribution learned by prediction models, the more significant the differences between the actual and predicted values are. Therefore, the basic idea of prediction-based anomaly detection methods is first to create a deep learning model. This model is then used to learn the normal data distribution to predict future data. During the model testing phase, the error between the original and predicted data points is compared to the threshold to determine if the data point is anomalous. Prediction-based methods are better able to adapt to changes in data distribution and complexity, thus improving the generalization ability of the model. However, their detection performance is significantly affected by the model's prediction ability and the accumulation of prediction errors. In addition, prediction-based methods tend to focus on

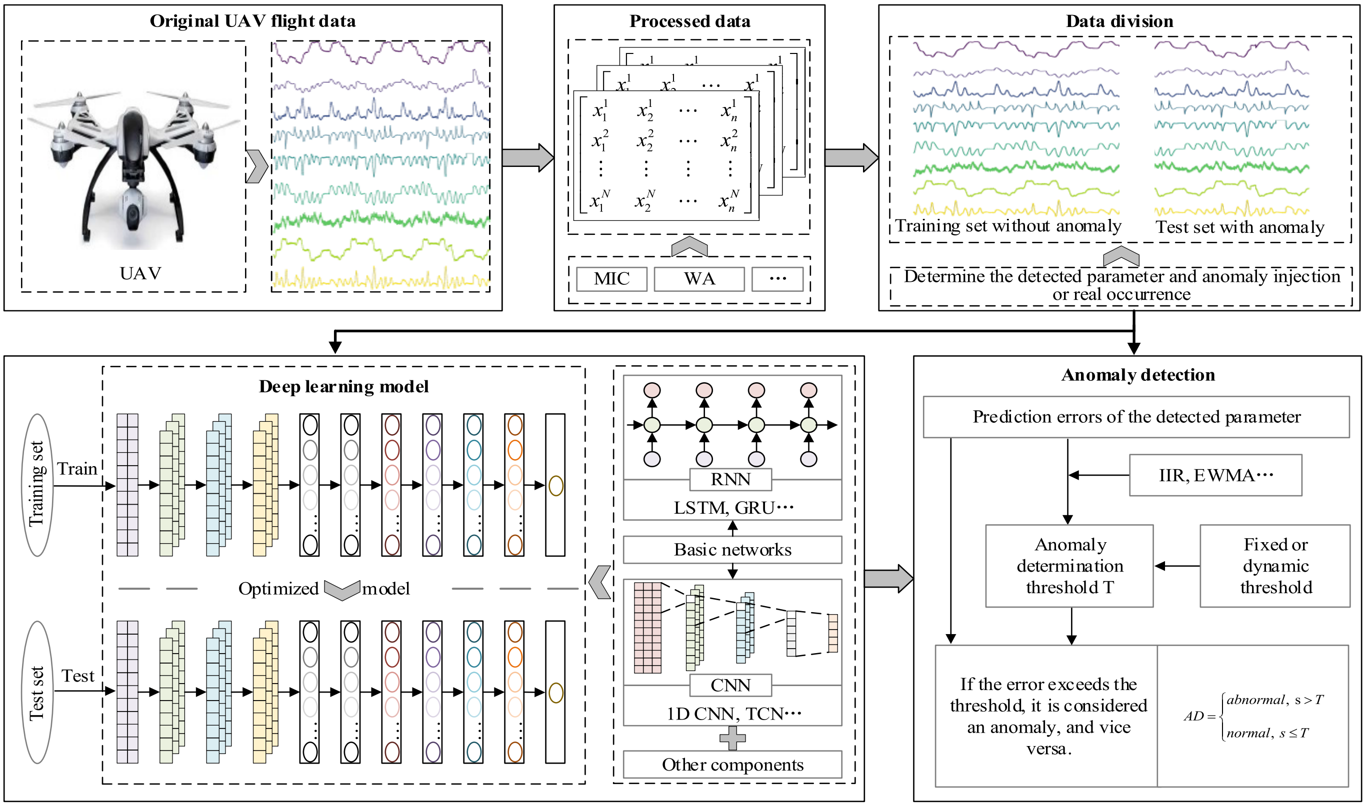

Fig. 5. General flow of prediction-based methods for UAV flight data anomaly detection.

monitoring a single parameter and lack an accurate grasp of the overall anomalies of the system.

Fig. 5 shows the general flow of prediction-based UAV flight data anomaly detection methods. In addition to normalizing the original UAV flight data using the max-min or Z-score methods, approaches such as the maximal information coefficient (MIC) [91], [104] and Pearson correlation coefficient (PCC) [64] can be used for parameter selection, or data can be denoised using wavelet analysis (WA) [98]. Next, the processed flight data are divided into training and test sets. In this phase, it is usually necessary to determine a detected parameter. The training set only contains normal data, while the test set contains anomalous data either injected artificially or actually occurs. Then, 1-D CNN-, temporal convolutional network (TCN)-, LSTM-, or gate recurrent unit (GRU)-based prediction models are used to model the flight data. These methods can be used alone, in combination, or with other components, such as graph attention network (GAT) [99] and attention mechanism (AM) [104], to construct prediction models that are trained and evaluated on training and test sets. Finally, anomaly detection is realized by comparing the prediction errors of the detected parameter with the threshold. In this stage, methods like the low-pass infinite impulse response (IIR) filter [63] and exponentially weighted moving average (EWMA) [99] can be used to smooth the prediction errors or dynamic thresholds can be used to improve anomaly detection performance. Table I lists the prediction-based anomaly detection methods, including critical information such as paper, year, paper type, method, data type, input data, and detected component (parameter).

1) RNN-Based Anomaly Detection Methods: Traditional RNN [105] suffers from problems like gradient vanishing and gradient explosion, which limits its performance on long sequence data [106]. To overcome these problems, existing studies mainly use variants of RNN like LSTM, GRU, and bi-directional LSTM (BiLSTM). Wang et al. [95] designed an LSTM-based prediction model for detecting anomalies in UAV sensor data, which successfully identified all anomalies in the north speed and pneumatic lifting speed. Point anomalies are relatively easily identified and detected as they often stand out clearly in data. However, more complex anomaly patterns, such as bias or drift anomalies, may require more effective detection strategies. As an effective solution, Wang et al. [63] chose the roll rate generated by the gyroscope sensor as the detected parameter and proposed a fault detection method based on LSTM with residual filtering (LSTM-RF). Experiments were conducted on simulated and real UAV flight data using parameters like roll angle, pitch angle, and yaw angle as model inputs, which showed that the average accuracy and area under the curve (AUC) of the method in dealing with bias and drift faults exceeded 0.928 and 0.967, respectively. In [90], a fault detection model acceleration engine (FDMAE) approach was proposed, which included an LSTM-based prediction model, an IIR-based residual filtering method, a field-programmable gate array (FPGA) acceleration method, and a PCA-based pruning method. This approach used GPS altitude, GPS longitude, pitch rate, and other parameters related to the position and attitude control of the UAV as model inputs and achieved accuracy and AUC of 0.986 and 0.998 for the roll rate with injected bias fault, respectively. Similarly,

TABLE I
LITERATURE RELATED TO PREDICTION-BASED ANOMALY DETECTION METHODS IN RECENT YEARS*

Paper	Year	Paper Type		Method		Data type	Input data	Detected component (parameter)
		C	J	MN	KC			
[63]	2019		✔	LSTM-RF	LSTM and IIR	Real and simulated data	Roll angle, pitch angle, yaw angle, etc.,	Sensor (roll rate)
[95]	2019	✔		LSTM	LSTM	Real data	North speed and pneumatic lifting speed	Sensor (north speed and pneumatic lifting speed)
[96]	2019		✔	-	1D CNN, PCA, logistic regression, and *k*-means	Real data	Gyroscope data, acceleration data, position data, etc.,	A single UAV
[90]	2020		✔	FDMAE	LSTM, PCA, IIR, and FPGA	Real data	GPS altitude, GPS longitude, pitch rate, etc.,	Sensor (roll rate)
[79]	2021		✔	STC-LSTM	ANNCA and LSTM	Real data	Pitch angle rate, right aileron command, yaw angle rate, etc.,	Sensor (roll angle)
[97]	2021	✔		CNN	CNN	Simulated data	Inertial measurement unit (IMU) data	Sensor
[62]	2021		✔	MOConvLSTM	LSTM and CNN	Real data	Airspeed, altitude, right aileron command, etc.,	Sensor (roll rate, airspeed, angle of attack, etc.,)
[91]	2021	✔		MIC-1DCNN	MIC and 1D CNN	Real data	Euler yaw angle, GPS east velocity, GPS latitude, etc.,	Actuator
[98]	2021	✔		Enhanced GRU	GRU and WA	Simulated data	Pitch, yaw, altitude, etc.,	Sensor (roll)
[64]	2022		✔	UA-LSTM	LSTM, PCC, and gaussian mixture model	Real and simulated data	Pitch angle, pitch rate, air speed, etc.,	Actuator
[99]	2022		✔	masked-SGAT-GRU	GRU, GAT, and EWMA	Real data	Roll angle, pitch angle, yaw angle, etc.,	Sensor (roll rate)
[100]	2022	✔		FTCN	TCN	Real data	Roll rate, pitch rate, yaw rate, etc.,	Sensor (pitch angle)
[101]	2022	✔		Stacked LSTM	LSTM and IIR	Real data	Roll rate, pitch rate, yaw rate, etc.,	Sensor (roll rate, *y*-velocity, etc.,)
[102]	2023	✔		LSTM	LSTM and IIR	Simulated data	Pitch angle, roll rate, actuator roll angle, etc.,	Sensor (roll angle)
[103]	2023		✔	-	BiLSTM and MIC	Simulated data	Airspeed, eastward velocity, roll angle, etc.,	Actuator
[104]	2023	✔		MICA-LSTM	LSTM, MIC, and AM	Simulated data	X-axis angular rate, euler roll angle, euler yaw angle, etc.,	Sensor (roll rate)

*C: conference; J: journal; MN: method name; KC: key component.

in [101] and [102], the authors also used LSTM prediction models and an IIR-based residual smoothing approach for UAV flight data anomaly detection. The former successfully detected all the point anomalies in the roll angle, while the latter achieved accuracy and F1 scores of 0.9615 and 0.9600 for parameters such as roll rate and y-velocity where anomalies existed. Chen et al. [98] utilized parameters such as pitch, yaw, and altitude as model inputs and denoised them using WA before model training. Then, they used an enhanced GRU prediction model to detect the roll parameter with bias fault.

The above studies often lack effective parameter selection when faced with multiple input parameters. Since numerous flight parameters exist, selecting appropriate parameters as model inputs is crucial. This is because unrelated parameters may have a negative impact on the model. Several studies have gradually realized the problem of complex high-dimensional parameter input and taken corresponding measures to deal with it. A typical example is a correlation analysis method based on PCC for selecting model input parameters [64]. In this example, a prediction model based on a novel uncertainty-aware LSTM (UA-LSTM) was proposed for modeling pitch angle, pitch rate, air speed, and other parameters that have a correlation with the actuator, and combined with dynamic thresholds for detecting the actuator injected with bias fault. However, PCC can only capture linear correlation of flight parameters, which means that the positive impact of some nonlinear correlation parameters on model performance may be lost. In this context, some studies introduced more sophisticated correlation analysis methods to address the problem. For example, Zhong et al. [79] proposed a spatio-temporal correlation-based LSTM (STC-LSTM) method for UAV flight data anomaly detection. They first selected seven parameters related to the roll angle as model inputs, such as pitch angle rate, right aileron command, and yaw angle rate, through artificial neural network correlation analysis (ANNCA). Then, they constructed an LSTM prediction model with a false positive rate (FPR) of 0, a false negative rate (FNR) of 0, and an accuracy of 1 for the roll angle injected with point, bias, and stuck anomalies. He et al. [99] used GAT to ignore irrelevant variables and finally selected 36 variables, such as roll angle, pitch angle, and yaw angle, which are significant to UAV flight as input parameters. Subsequently, they detected the roll rate injected with multiple fault types based on the proposed masked spatial GAT with the GRU (masked-SGAT-GRU) model. Apart from this, some information theory-based methods are also used for parameter selection. For example, Zhou et al. [104] proposed a sensor fault detection method based on MIC and LSTM with AM (MICA-LSTM). They first used roll rate as the detected parameter and selected seven parameters related to it using MIC, such as X-axis angular rate, Euler roll angle, and Euler yaw angle, as model inputs. Then, a prediction model was constructed based on LSTM and AM with a fault detection accuracy of more than 0.9900 for the roll rate injected with bias and drift faults. Although Keipour et al. [59] may lose some key nonlinear correlation parameter information compared to [79], [99], and [104], it could dynamically detect anomalies in the flight data. This is particularly important since UAV operating environments are often complex and variable and fixed thresholds often fail to change with dynamic flight changes. However, considering the complex relationship between UAV flight parameters, relying only on LSTM or GRU may lead to inadequate feature extraction, affecting the model's accuracy and generalization ability. In contrast, by combining GAT and AM, [99], [104] can perform finer feature extraction and modeling of UAV flight data. However, the increase in model complexity may further lead to an increase in computational cost, and thus the effectiveness of these methods in practical applications needs to be further validated.

The effectiveness of the above methods relies on sufficient data for model training. However, obtaining adequate flight data may be costly in practice. In recent research, Liu et al. [103] proposed an innovative cross-domain approach for UAV actuator fault detection. This method utilized parameters such as airspeed, eastward velocity, and roll angle as inputs to the BiLSTM prediction model and introduced a method to compute similarity metrics between different domains using MIC. The fault detection results on the actuator injected with bias and drift faults were better than 0.0250 for FPR, and the true positive rate (TPR) and accuracy were both higher than 0.9779. The uniqueness of this approach is that it alleviates the dependence on massive training data in the target domain and provides a more flexible solution for anomaly detection of UAV flight data with limited samples. However, this work did not explore the performance of the model with different fine-tuning samples. This is because in some cases, when a certain number of fine-tuning samples are reached the model can be trained directly without transfer learning to achieve satisfactory results.

2) CNN-Based Anomaly Detection Methods: Unlike RNN methods like LSTM, GRU, and BiLSTM, CNN captures local features and patterns in the input data through its convolution and pooling layers [107], [108]. In addition, CNN can be computed in parallel, which is more efficient when dealing with large-scale data. For example, Ahn et al. [96] used 1-D CNN and a fully connected multilayer perceptron to detect a single UAV anomaly in swarm UAVs by modeling flight data such as gyroscope, acceleration, and position. Similarly, Galvan et al. [97] designed a CNN-based prediction model and utilized inertial measurement unit (IMU) sensor data as model input. The experimental results showed that the AUC for different components of the IMU sensor injected with anomaly was 0.937. In [91], a fault detection method based on MIC and 1-D CNN (MIC-1-D CNN) was proposed, which utilized MIC to select the parameters, such as Euler yaw angle, GPS east velocity, and GPS latitude, as model inputs. Then, a prediction model based on 1-D CNN was used to detect the actuator's bias and drift faults. This method maintained a lower FPR while its TPR and AUC exceeded 0.9400 and 0.9800, respectively, and possessed a faster detection speed.

However, CNN mainly focuses on local feature extraction. This may result in CNN ignoring long-term dependencies and contextual relationships when processing time-series data. As an alternative to CNN, You et al. [100] proposed a UAV sensor anomaly detection method based on fine-tuned TCN (FTCN). The method utilized ten variables like roll rate, pitch rate, and yaw rate as model inputs and achieved an accuracy of 0.9476 on the pitch angle with the injected anomaly. Another approach is to combine CNN and LSTM to construct a prediction model, such as the multioutput convolutional LSTM (MOConvLSTM) method in [62]. This method modeled the input parameters such as airspeed, altitude, and right aileron command, and effectively detected the parameters like roll rate, airspeed, and angle of attack with anomalies. Compared with the previous studies, this work combined the advantages of CNN in local feature and LSTM in temporal feature extraction to better extract spatio-temporal features of UAV flight data, thus improving anomaly detection performance.

C. Reconstruction-Based Anomaly Detection Methods

Reconstruction-based approaches map input data to the latent space and learn how to reconstruct it accurately to detect anomalies [109]. These approaches can effectively capture anomaly patterns in the data and focus more on monitoring the overall anomalies of the system. When there are anomalies in the input data, it becomes exceptionally difficult to accurately reconstruct the original data. This is because the latent space may lose information about rare anomalies, leading to increased reconstruction errors [94], [110]. However, reconstruction-based approaches often require more computational resources than prediction-based methods, making them possibly challenging when dealing with large-scale data. In addition, information may be lost during the reconstruction process, especially if the data are highly complex or noisy, which may lead to a high false alarm rate.

Fig. 6 illustrates the general flow of the reconstruction-based methods. Specifically, in the data preprocessing stage, the input data can be denoised using the Savitzky–Golay (S-G) filter [88] in addition to normalizing the original flight data. Next, the processed data are divided into training and test sets. It is worth emphasizing that reconstruction-based methods usually do not need to determine the detected parameter because they focus on multivariate anomaly detection, as previously mentioned. Then, the deep learning models are trained and evaluated with training and test sets, including LSTM-AE [88], [89], [111], [112] or 1-D CNN-based VAE [92]. Finally, the anomaly detection of UAV flight data is realized by comparing the reconstruction errors with the threshold. Table II lists the reconstruction-based methods for UAV flight data anomaly detection in recent years.

1) AE-Based Anomaly Detection Methods: Sequential information in time series data is important for data reconstruction. Traditional AE may ignore this sequential information when reconstructing the input data [115], [116]. Therefore, a common practice is to combine AE with LSTM. This is because LSTM can more effectively capture flight data's temporal patterns and regularities. For example, Bae and Joe [111] used an LSTM-AE reconstruction model for different anomaly detection tasks through a targeted selection of parameters, such as position, battery, and attitude, as model inputs. The AUC of this method was more than 0.9200 for low-level and high-level anomaly detection. Similarly, Gao et al. [113] used navigation altitudes from six flights as inputs to an LSTM-AE reconstruction model, where the normal flights were used for model training and the abnormal flights with anomaly were used for evaluating the model. The average FI score and accuracy of LSTM-AE exceeded 0.93 and 0.89, respectively. Another approach is to utilize BiLSTM and CNN to construct an AE model. BiLSTM has a better contextual understanding

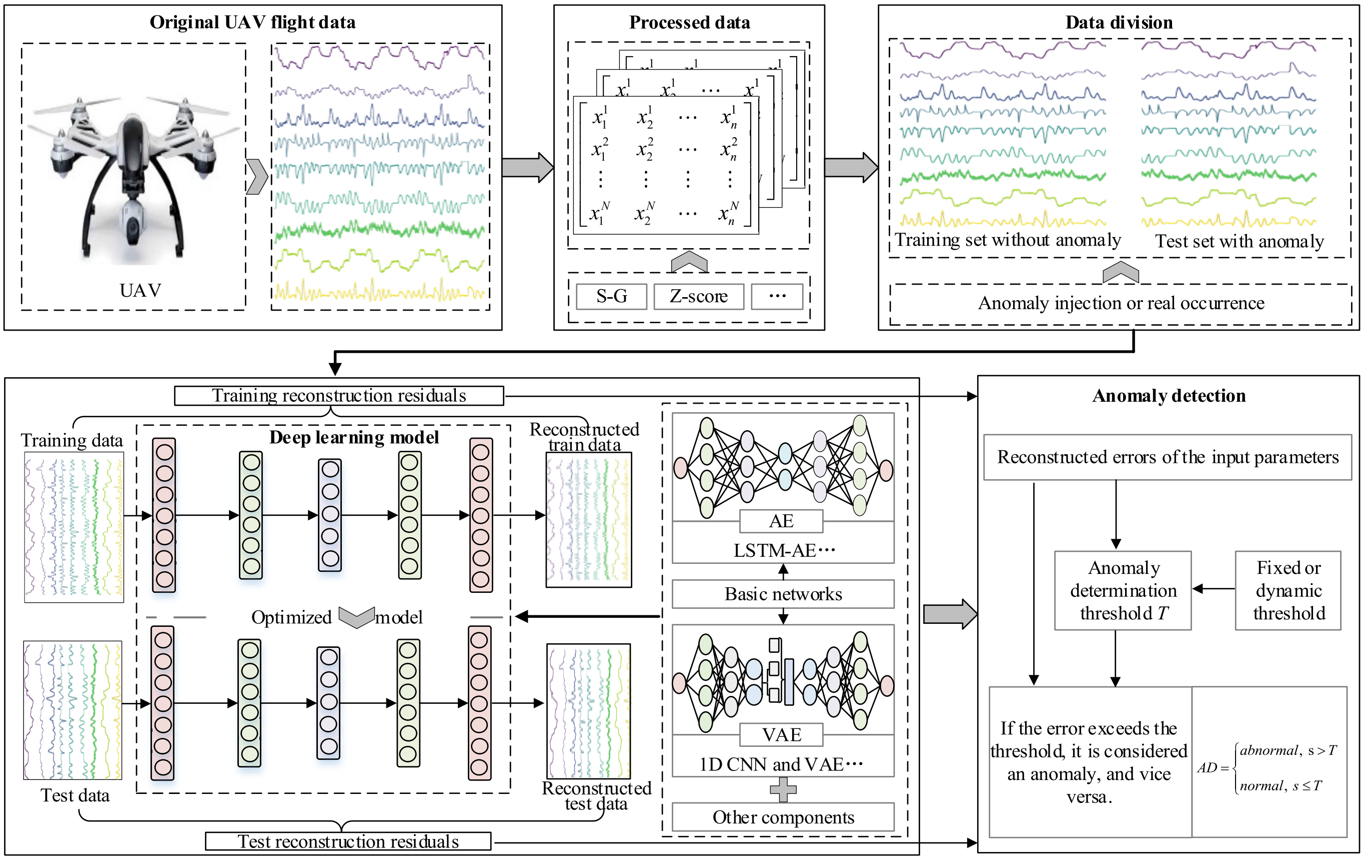

Fig. 6. General flow of reconstruction-based methods for UAV flight data anomaly detection.

TABLE II
LITERATURE RELATED TO RECONSTRUCTION-BASED ANOMALY DETECTION METHODS IN RECENT YEARS*

Paper	Year	Paper Type			Method		Data type	Input data	Detected component (parameter)
		C	J	P	MN	KC			
[92]	2020	✔			-	1D CNN and VAE	Real data	Accelerator data, magnetometer data, barometer data, etc.,	A single UAV
[111]	2020	✔			LSTM-AE	LSTM and AE	Real data	Position, battery, attitude, etc.,	Sensor (position, battery, attitude, etc.,)
[89]	2022		✔		LSTM-AE	LSTM and AE	Real data	Data of power and pulse-width modulation value of each motor	Propeller, motor, frame (power and pulse-width modulation)
[112]	2022			✔	LSTM-AE+DT+DW	LSTM, AE, and PCA	Real data	ALFA dataset	Engine
[93]	2023	✔			AE and VAE	AE and VAE	Real data	ALFA dataset	Left rudder, right rudder, left aileron, etc.,
[88]	2023		✔		STC-LSTM-AE	LSTM, AE, S-G, and MIC	Real data	GPS latitude, euler roll angle, X-axis acceleration, etc.,	Sensor (GPS altitude and NAV altitude)
[113]	2023		✔		-	LSTM and AE	Real data	Navigation altitude	Sensor (navigation altitude)
[69]	2023		✔		AutoEnc	CNN, BiLSTM, FPGA, and AE	Real and simulated data	Accelerometer, gyroscope, and magnetometer data	Sensor
[114]	2023		✔		GNF	BN, Transformer, and GCN	Real data	Roll, pitch, yaw, etc.,	Compass, GPS, etc.,

*P: preprint.

when processing temporal data compared to LSTM [117]. For example, Sadhu et al. [69] constructed an AE model using BiLSTM and CNN and utilized accelerometer, gyroscope, and magnetometer data as model inputs with an anomaly detection accuracy of over 90%. Although AE can filter out some noise, its effectiveness in suppressing random noise may be limited. Considering this challenge, an STC-LSTM and AE (STC-LSTM-AE) was proposed in [88], which denoised the determined parameters based on MIC, such as GPS latitude, Euler roll angle, and X-axis acceleration, by using S-G before LSTM-AE model training. The method effectively reduced the effect of random noise and achieved an anomaly detection accuracy as high as 98.75%.

However, the studies mentioned above mainly used fixed thresholds, which may not be effectively adapted to the dynamics and complexity of the UAV flight environment, and thus may lead to a higher false alarm rate. To address this issue, some studies adopted dynamic threshold generation methods that adaptively adjust the thresholds for more accurate anomaly detection. For example, Jeon et al. [89] utilized the power and pulsewidth modulation value of each motor as input to the designed LSTM-AE model and used an adaptive decision score method to detect manually created propeller, motor, and frame anomalies. The experimental results showed that the average specificity and sensitivity of the method were 98.6% and 90.3%, respectively. Similarly, Arce et al. [112] focused on detecting engine fault in the ALFA dataset [11] based on an LSTM-AE model with dynamic thresholding and dynamically weighted loss function (LSTM-AE + DT + DW). Unlike [89], [112], Ma et al. [114] introduced a more advanced Transformer as a coding module and combined it with BN and graph convolutional network (GCN) and proposed an anomaly detection method based on graphical normalizing flows (GNF). The method used parameters like roll, pitch, and yaw, as model inputs and combined them with dynamic thresholds to detect abnormal components such as Compass and GPS. In particular, this work collected and organized the first dataset of small unmanned aerial systems (sUASs), including 41 flight logs labeled with various anomaly types. However, the model may have a high computational cost and model complexity due to the use of multiple modules [114].

2) VAE-Based Anomaly Detection Methods: Compared with AE, VAE introduces a hidden variable distribution [118]. This allows VAE to take into account the probabilistic structure in the latent space, making it more expressive and interpretive, thus better capturing the underlying patterns and variations in the input data [119]. In recent years, VAE has also been actively introduced into the UAV flight data anomaly detection field. For example, Dhakal et al. [93] detected abnormal components, such as the left rudder, right rudder, and left aileron, using the ALFA dataset as input to AE and VAE models. The results showed that the VAE-based method could effectively detect anomalies with an average accuracy of 95.6%. However, as revealed in this work, it was mainly limited to offline operation and could not fulfill the needs of real-time anomaly detection. Different from traditional VAE, Ahn [92] constructed a 1-D-CNN-based VAE model to model the signals collected by sensors, such as accelerator, magnetometer, and barometer, to detect anomalies in a single UAV. However, the method may result in higher computational costs and resource requirements for model training due to the use of a deeper network structure.

V. Commonly Used Anomaly Determination Thresholds

Thresholds play a vital role in anomaly detection and directly affect model performance and reliability [61]. Thresholds that are too high or too low may result in a higher false alarm rate [120]. Therefore, it is important to choose proper thresholds to ensure the model is robust and reliable in practical applications. Therefore, we analyze and summarize the threshold calculation methods used in existing studies more comprehensively, aiming to provide a reference for subsequent research in threshold selection.

A. Mean Squared Error

Mean square error (mse) is a metric that is used to measure the difference between predicted or reconstructed and actual data [121]. It first calculates the sum of squares of the residuals for each data sampling point and then averages them, i.e., $\text{mse} = 1/n \sum_{i=1}^{n} (\hat{y}_i^{\text{tr}} - y_i^{\text{tr}})^2$, where $\hat{y}_i^{\text{tr}}$ and y_i^{tr} are the predicted or reconstructed and the actual data of the original ith sample in the training set, respectively, and n is the sample length. MSE as a threshold is commonly used in reconstruction-based methods [88], [93], [113]. The advantage of mse is that it is simple to calculate and very sensitive to rapidly fluctuating anomalies. This sensitivity allows mse to detect small but significant changes in the data to take the necessary action in advance to ensure system reliability and safety. However, this method requires the model to be very precise in prediction or reconstruction, which may cause the model to be too critical of some otherwise decent results, thus reducing the model's accuracy and robustness. Therefore, there is a trade-off between simplicity and sensitivity to anomaly when using mse as the anomaly detection threshold.

B. N-Sigma

N-sigma is a commonly used threshold calculation method [122]. It first requires calculating the mean $\mu = 1/n \sum_{i=1}^{n} (\hat{y}_i^{\text{tr}} - y_i^{\text{tr}})$ and standard deviation $\sigma = 1/(n-1) \sum_{i=1}^{n} [(\hat{y}_i^{\text{tr}} - y_i^{\text{tr}}) - \mu]^2\}^{1/2}$. Then, the threshold $T = \mu \pm l\sigma$, i.e., $[\mu - l\,\sigma, \mu + l\sigma]$, is obtained, where l is the coefficient that is usually set according to the confidence level required. For example, when a 99% confidence level is required, l can be set to 2.6 [63]. Prediction-based methods mostly use n-sigma as the anomaly detection threshold [63], [79], [90], [95]. Compared with mse, n-sigma can adjust the value of parameter l to meet the needs of detecting more complex anomaly patterns. This flexibility allows n-sigma to better recognize anomalies when dealing with various complex data. Although the calculation of n-sigma is also relatively simple, it assumes that the data distribution is normal, which may not hold true in many practical applications. For nonnormal distribution data, n-sigma may not be able to accurately identify anomalies, leading to an increase in false or missed alarms [123]. Therefore, when dealing with data with nonnormal or complex distributions, it is necessary to combine other methods or adjust the strategy to obtain more accurate detection results.

C. Dynamic Thresholds

Compared with fixed thresholds, dynamic thresholds can be more flexible to adapt to complex flight environments, thereby improving model detection performance [64], [89], [112], [114]. For example, in [112], a static threshold constant $L = \mu_{\text{train}} + \sigma_{\text{train}}$, the mean loss value for the j instances $M = 1/j \sum_{i=n-j}^{n} x_i$, and the standard deviation $S = \sigma(x_{n-j}, \ldots, x_{n-1})$ are first computed, where μ_{train} and σ_{train} are the mean and standard deviation of the training reconstruction loss, and x_i is the loss of the ith data point. Then, the threshold $T_n = T(x_n) = W_y L + W_z(M + S)$ for the nth instance is obtained, where W_y and W_Z are the weight constants of L and M, respectively. However, this approach requires dynamic calculation of the mean loss and standard deviation, which is computationally expensive when dealing with large-scale datasets. Especially in real-time or near real-time anomaly detection tasks, it can significantly increase the system load and affect the processing efficiency with frequent computations. Other dynamic thresholds, such as [64] and [89], similarly require dynamic calculation of the mean and standard deviation to determine if the current data point is abnormal. Although using the sliding window to obtain thresholds can reduce computational overhead, there is a trade-off between time and space complexity in determining the window size to ensure that anomalies can be accurately detected without losing important information [114].

VI. Future Perspectives

Existing studies have made some progress in coping with the characteristics of complex high dimensional and random noise in UAV flight data, deep learning model construction, and threshold calculation. For example, researchers use S-G [88], WA [98], IIR [63], [101], [102], and EWMA [99] to denoise the data in the preprocessing stage or smooth the residuals in the anomaly detection stage to minimize the effect of random noise. Meanwhile, some studies utilize PCC [64], ANNCA [79], and MIC [88], [104] to select features with correlation as inputs from high-dimensional parameters to improve model performance. For deep learning model construction, some advanced methods are proposed, such as MOConvLSTM [62], masked-SGAT-GRU [99], MICA-LSTM [104], deep CNN and LSTM-based neural network [69], and GNF [114], for better modeling and feature extraction of flight data. In terms of threshold computation, since 2022, researchers have gradually adopted dynamic thresholds for anomaly detection in UAV flight data, which improves the flexibility of anomaly detection in complex conditions [64], [89], [112], [114]. Despite this, there are still some issues and challenges that need to be addressed. Therefore, in this section, we provide some directions for future research that are worthwhile for reference.

A. Critical Parameter Identification

Current studies focus on the model's ability to detect anomalies and lack a comprehensive understanding of the deeper causes behind anomalies [63], [64], [79], [88], [89], [90], [114]. Anomalies that occur in UAVs may be caused by one or more flight parameters. Identifying flight parameters that contribute significantly to anomalies is of great reference value and significance for UAV maintenance. An information theory approach, nonparametric estimation based on copula entropy, can be first used to measure the mutual information (MI) values between variables. These MI values are then used as the contribution degree to anomalies that caused the system to occur, thus identifying the monitoring parameters associated with anomalies [124]. Meanwhile, the monitoring parameters' scores contributing to anomalies can be calculated by a multiple self-AM to identify critical parameters [125]. It utilizes an advanced neural network to capture the complex relationships between variables more accurately, providing deeper insights into explaining the causes of anomalies. Further, the anomaly scores can be transformed using a multivariate Gaussian distribution to identify the critical parameters contributing to anomalies [110]. Therefore, future research can actively carry out critical parameter identification studies to provide more targeted guidance for the maintenance and optimization of UAVs.

B. Adaptive Anomaly Detection for Multivariate UAV Flight Data

Existing prediction-based methods focus mainly on anomaly detection of univariate flight parameters, which have certain limitations in practical applications [63], [64], [90], [91], [95], [98], [99], [100]. In practice, anomalies that occur in UAVs usually cause multiple flight parameters to deviate from the expected values, making these methods lack a comprehensive grasp of UAV anomalies. Despite the reconstruction-based methods being able to achieve multivariate anomaly detection, they are slightly less effective in modeling and feature extraction for complex flight data. A good anomaly detection performance relies on the accurate reconstruction or prediction performance of models. The key is the need for finer feature extraction and modeling of the complex relationships of UAV flight data. As a revolutionary deep learning architecture, Transformer can effectively capture long-range dependencies in sequences and transform them into meaningful feature representations [126]. Therefore, UAV flight data can be modeled with the help of a Transformer to extract richer and more abstract features. These features can better reflect the complex relationship of UAV flight data and provide stronger support for the subsequent anomaly detection task. In addition, UAV flight environments are complex and variable, which poses a challenge to the adaptability of traditional statistical threshold-based methods. Considering the computational efficiency, a dynamic threshold generation method based on SVR can be used [124]. In particular, the method can effectively cope with the dynamic changes of flight data without considering the data distribution and improve the model's accuracy and robustness.

C. Real-Time Anomaly Detection Research Under Limited On-Board Resources

In recent years, many studies have utilized more complex deep learning models to extract complex spatio-temporal correlation features of UAV flight data to improve model performance. In this case, these models may suffer from high complexity and computational cost [62], [99], [104], [114]. Therefore, although these methods have been proven to be effective in anomaly detection, they lack practical application scenario constraints, such as the accuracy and real-time anomaly detection problems under limited on-board computing resources, making the practicality and effectiveness of these methods need further verification. To address this issue, lightweight models can be considered, such as compact neural networks [127], to reduce computation and memory usage while maintaining the excellent performance of the model. It is possible to use PCA to prune the model and reduce the computational effort of the model, thus improving the efficiency of model inference [90]. The model inference process can be also accelerated using FPGA [69], [90]. FPGA can real-time inferences in resource-constrained environments due to its processing capability and low power consumption, making the model more suitable for situations where on-board computing resources are limited. In addition, a novel distributed redundant flight control computer architecture can be adopted [17]. This architecture includes a distributed task scheduling and communication model and an optimal static scheduling and real-time analysis algorithm, etc., which can detect anomalies or faults in real time while maintaining low power consumption.

D. Model Generalization and Interpretability Research

Model generalization and interpretability are key challenges in applying deep learning to engineering practices. For model generalization, most current methods focus on model training and construction for specific UAVs or problems, resulting in limited model generalization. Since UAV flight data may be affected by various factors, a model trained for a specific dataset may not cope with anomalies in datasets from other environments, resulting in its performance degradation in new environments. To improve the model generalization, the dataset size can be expanded to cover a wider range of scenarios to train the model. This allows the model to be exposed to more diverse contexts during training and improves its adaptability. Second, developing accurate deep learning models is also an effective way to enhance the model generalization. For example, it is possible to utilize AM to better handle long-term dependencies and enhance the learning of key features, thereby improving the model's prediction or reconstruction accuracy of the data [128]. Furthermore, transfer learning [129] can also be effective in improving the model's generalizability by sharing knowledge among different tasks. In terms of model interpretability, traditional methods, such as sensitivity analysis, the partial dependence test [130], and local interpretable model-agnostic explanations (LIME) [131], can improve model global or local interpretability. In addition, the more advanced layer-wise relevance propagation method can be used to reveal how the relationship between different input features at different time steps affects the model's output, thus enhancing model interpretability [132].

VII. Conclusion

Flight data anomaly detection is important and significant to ensure the safety and stability of UAVs. Deep learning methods have been widely used in the field of UAV flight data anomaly detection and have gradually become mainstream. Therefore, this article presented a comprehensive review of the research progress of deep learning-assisted UAV flight data anomaly detection. First, we presented the multistage, multisource, and time-varying characteristics of UAV flight data and described point, bias, drift, stuck, and compound anomaly types. Then, the research progress of prediction- and reconstruction-based deep learning methods was analyzed and summarized in detail, focusing on RNN-, CNN-, AE-, and VAE-based methods. Finally, several insightful future research directions were given, including critical parameter identification, adaptive multivariate anomaly detection, real-time anomaly detection research, and model generalizability and interpretability research. These directions are expected to provide new theoretical and technical support for building more robust and reliable UAV flight data anomaly detection methods in the future.

This work aims to lay the foundation for future research and provide insights into developing new innovative methods and techniques of UAV flight data anomaly detection. Meanwhile, we expect this work to encourage and inspire more researchers to conduct in-depth studies to address current challenges and promote greater progress in the field.

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