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A survey of unmanned aerial vehicle flight data anomaly detection: Technologies, applications, and future directions

YANG Lei[1], LI ShaoBo[1,2*], LI ChuanJiang[1], ZHANG AnSi[1,2] & ZHANG XuDong[1]

[1] School of Mechanical Engineering, Guizhou University, Guiyang 550025, China;
[2] State Key Laboratory of Public Big Data, Guizhou University, Guiyang 550025, China

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Flight data anomaly detection plays an imperative role in the safety and maintenance of unmanned aerial vehicles (UAVs). It has attracted extensive attention from researchers. However, the problems related to the difficulty in obtaining abnormal data, low model accuracy, and high calculation cost have led to severe challenges with respect to its practical applications. Hence, in this study, firstly, several UAV flight data simulation softwares are presented based on a brief presentation of the basic concepts of anomalies, the contents of UAV flight data, and the public datasets for flight data anomaly detection. Then, anomaly detection technologies for UAV flight data are comprehensively reviewed, including knowledge-based, model-based, and data-driven methods. Next, UAV flight data anomaly detection applications are briefly described and analyzed. Finally, the future trends and directions of UAV flight data anomaly detection are summarized and prospected, which aims to provide references for the following research.

unmanned aerial vehicle (UAV), flight data, anomaly detection, data-driven

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1 Introduction

As an important area of future technology competition among countries, unmanned aerial vehicle (UAV) technology has applications in medical [1,2], agriculture [3,4], environmental monitoring [5,6], search and rescue operations [7], and disaster management [8]. Hence, sales and production value of UAVs have been increasing on an annual basis [9]. Therefore, given the increasingly prominent role of UAVs in various fields and their importance in economic development, higher requirements are placed on their safety and reliability, especially in complex operating environments [10]. However, when compared with manned aircraft, the safety and reliability of UAVs are compromised by the following shortcomings: (1) lack of pilots' real-time observation, rapid decisions, and responses; (2) limited size, weight, and power consumption; and (3) non-redundant or low-redundant design [11,12]. These factors lead to higher incidence of UAV accidents when compared with that of manned aircraft. Based on American statistics, the accident rate of UAVs is 100 times that of general aircraft [13], which in turn causes serious economic losses to relevant enterprises.

In recent years, UAV accidents have been frequently reported in China and abroad. The U.S. Air Force Accident Investigation Board (AIB) accounted accidents involving 11 types of UAVs, including the RQ/MQ-1 Predator, RQ-4 Global Hawk, and MQ-9 Reaper. The survey showed that 21 accidents were due to human factors, 56 accidents were due to system faults, and 4 accidents were due to environmental and other factors [14]. Based on the civil UAV accidents data acquired by the U.S Federal Aviation Administration (FAA)

*Corresponding author (email: lishaobo@gzu.edu.cn)

via the UAS&I platform [15], 104 accidents, involving 44 types of UAVs, occurred. Among them, the number of accidents caused by faults in UAV system was as high as 90, accounting for 86.54% of the total accidents. In June 2016, institutions in China counted 47 domestic UAV accidents caused by faults among which DJI UAVs caused 24 accidents. According to Shenzhen DJI Innovation Technology Co., Ltd., the manufacturer of DJI UAVs, more than 85% of UAV accidents are due to user misuse, and only a few of them were due to component faults and other reasons involving. Furthermore, the flight status information of UAVs is primarily determined by flight data that include altitude, speed, attitude angle, and other flight parameters. They comprehensively reflect the operating status of the UAV's key components and operators' operation information [16]. With the continuous accumulation of historical UAV flight data, processing and analyzing their abnormal data information have become the primary means for evaluating their flight quality, analyzing the causes of accidents, enhancing work efficiency, and improving their design [17]. Therefore, researching effective UAV flight data anomaly detection methods is an imperative way for improving the safety performance of UAVs [18].

Many researchers reviewed flight data anomaly detection. Peng et al. [9] reviewed the classification-based, clustering-based, statistics-based, regression-based, and domain-based flight data anomaly detection methods, and indicated research directions that should be focused in the future. Peng et al. [19] conducted a comprehensive review of the field of anomaly detection in spacecraft telemetry data, including its basic connotation, methods, and application status. Das et al. [20] and Basora et al. [21] compared and analyzed different flight data anomaly detection methods from an algorithmic perspective. In an extant study, Igenewari et al. [22] reviewed the strengths and weaknesses of current anomaly detection methods and benefits of hybrid anomaly detection methods. Khan et al. [23] described the current literature on solutions to detect anomalies in known and unknown flight data. Furthermore, they tested the practicability of the isolation forest algorithm in engineering applications based on the simulation data of aviation propulsion systems. However, most of the aforementioned studies focused on flight data anomaly detection for manned aircraft as opposed to UAVs. Compared with manned aircraft, UAV flight data anomaly detection is more challenging. The main reasons include: (1) management and support for the production of the UAV industry is not perfect, and there is no flight operational quality assurance (FOQA) [24] program similar to the civil aviation field. There is also a lack of a standardized and unified historical flight database. (2) Current anomaly detection method is overly dependent on the analysis of ground control stations. Given the limitation in the communication ability of the network during the flight of UAV, the ground station cannot obtain comprehensive flight statuses of UAV in real-time. If anomalies in UAV flight data are not detected and resolved in time, then there will be significant safety hazards, which can result in serious accidents. Consequently, in this study, we attempt to provide a comprehensive overview of the technologies, applications, and future directions of UAV flight data anomaly detection to offer some references for future researchers.

The organization of the paper is as follows. In Section 2, we describe the basic concept of anomalies, UAV flight data content, flight data collector, and public UAV flight data anomaly detection datasets-ALFA and University of Minnesota UAV real flight datasets. In Section 3, we discuss the advantages and disadvantages of UAV flight data simulation software. In Section 4, we analyze and summarize the research progress of UAV flight data anomaly detection technologies, including knowledge-based, model-based, and data-driven methods. In Section 5, we discuss some UAV flight data anomaly detection platforms and frameworks, along with the status of applications at research institutions at home and abroad. In Section 6, we present a brief overview of future research challenges, and in Section 7 we conclude the paper.

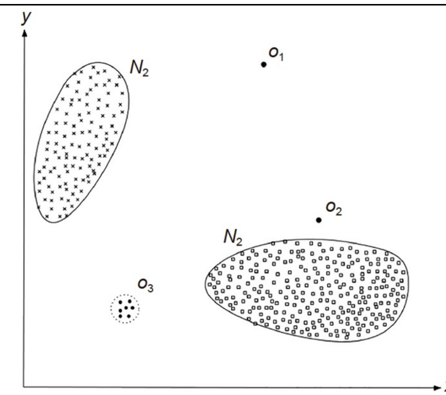
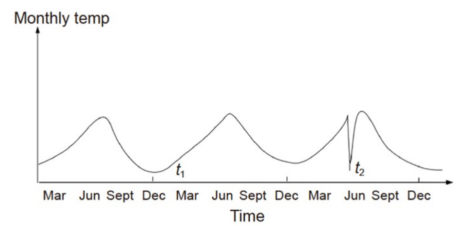
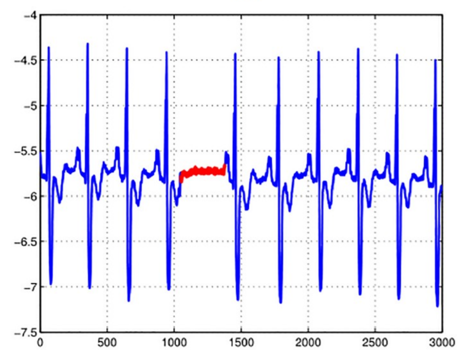
2 UAV flight data anomaly

2.1 Basic concepts of anomalies

Hawkins [25] proposed that certain data types in a set are abnormal, which are not due to random deviations but due to completely different mechanisms. Keogh et al. [26] further introduced the concept of time series anomaly based on the chronological order of anomalies. They proposed that it did not involve the size of the sliding window, and there is no guarantee that the abnormal expansion between high-dimensional and low-dimensional data features is consistent. Although there is currently no clear definition of anomaly, it can be considered as a pattern as opposed to normal. Furthermore, data are the expression form and carrier of information and most of the behaviors expressed in the data are regarded as normal. However, a few data behaviors that do not conform to the norms considered as abnormal [27]. The types of abnormal data behaviors can be categorized as point anomalies [28], contextual anomalies [29], and collective anomalies [30]. Their types, meanings, and examples are listed in Table 1.

UAV flight data are typical time series data that are sampled based on a time sequence. Therefore, according to the definition of anomalies in time series, the anomalies of UAV flight data can be classified into flight level anomalies and instantaneous anomalies [9]. Flight level anomalies refer to the abnormal sequence or subsequence of flight data that are also termed as collective anomalies (as shown in Figure 1).

Table 1 Types, meanings, and examples of anomalies [31]. Copyright©2009, Association for Computing Machinery (ACM)

Type	Meaning	Example
Point anomalies	Data points are considered independent in the time series, which significantly differs from other data points.	
Contextual anomalies	Several abnormal events in the entire time series use point anomalies, which make it extremely difficult to identify the events associated with their decisions data.	
Collective anomalies	Some abnormal data points that are significantly different from others in a dataset.	

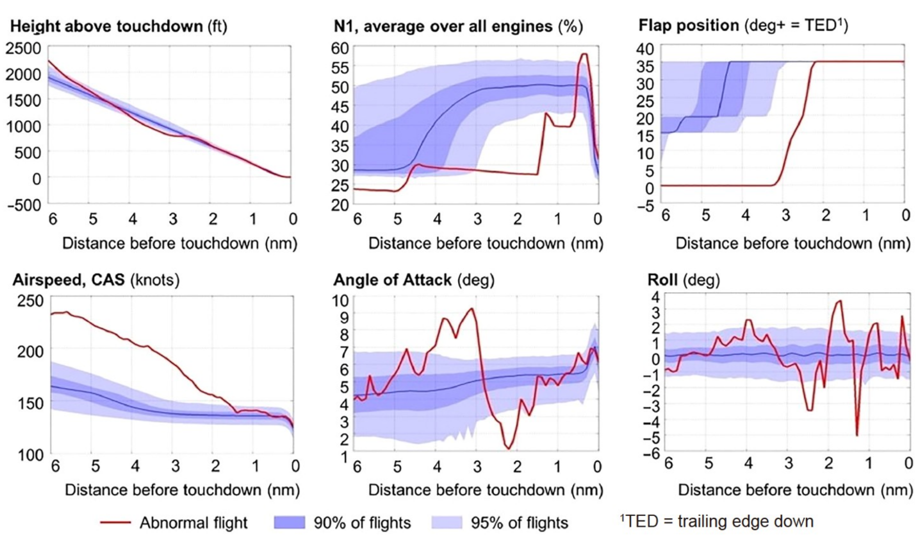


Figure 1 (Color online) Example of fight level anomalies [32]. Copyright©2016, Elsevier.

Instantaneous anomalies refer to abnormal points in the in-flight data that deviate from expected values. Given that the adjacent points of the time series of in-flight data are dependent on time or space, they can also be referred as contextual anomalies. Figure 2 shows an example of instantaneous anomalies in-flight data.

As shown in Figure 1, most of the flight data of a specific sortie differs from others under the same parameter settings. This can be caused by the instability during landing [32]. Figure 2 shows four abnormal flight data parameters (navalt, navvd, navve, and navvn at the top of Figure 2) and anomaly score (at the bottom of Figure 2). Hence as the score increases, the probability of becoming an outlier increases. This is potentially due to the failure of GPS and navigation filters [33]. The meanings of the relevant parameters mentioned above will be introduced in Section 2.3.

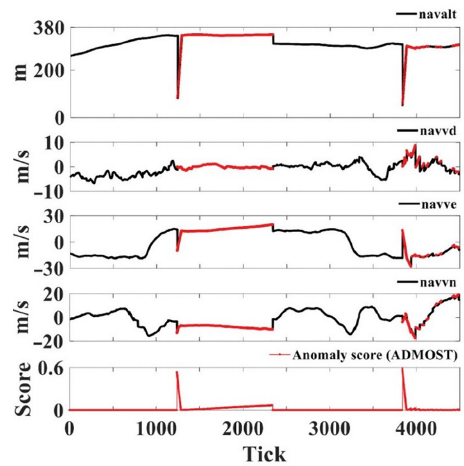


Figure 2 (Color online) Example of flight data instantaneous anomalies [33]. Copyright©2018, Institute of Electrical and Electronics Engineers Inc.

2.2 Overview of UAV flight data

Data is the information source of an analysis system. In the era of big data, data is particularly important. To detect abnormal flight data of UAVs, data collection should be performed first. UAV flight speed, acceleration, heading angle, pitch angle, and other parameters during flights are recorded using various sensors and measurement devices (as shown in Figure 3) and are sent to the airborne recording system in a specific data format for real-time storage. The UAV flight data acquisition process is shown in Figure 4. The data collectors involved are the core components of the flight data acquisition system, such as the flight data recorder (FDR) [34], quick access recorder (QAR) (termed as the black box on the plane) [35,36], MMSC-800, AIFTDS-8000, and DAMIEN-V1. Their advantages are listed in Table 2.

Given the aforementioned flight data collectors, FDR can be used to acquire various flight parameters for UAVs. However, inadequate recording parameters and insufficient reliability of the protective device imply that its recorded data cannot be preserved accurately. MMSC-800, AIFTDS-8000, and DAMIEN-Vl exhibit excellent data acquisition capabilities, but they are difficult to assemble. Conversely, QAR has attracted considerable attention for its speed and simplicity in accessing raw flight data [37–39]. It is often used in flight simulation and reproduction, aircraft maintenance, safety quality assessment, and accident factor investigation by airlines and related departments. Furthermore, QAR data can objectively and comprehensively display the actual flight position of UAVs, including detailed flight data, intuitive charts, and animations, which can enhance incident investigation efficiency. During the entire flight phase, var-

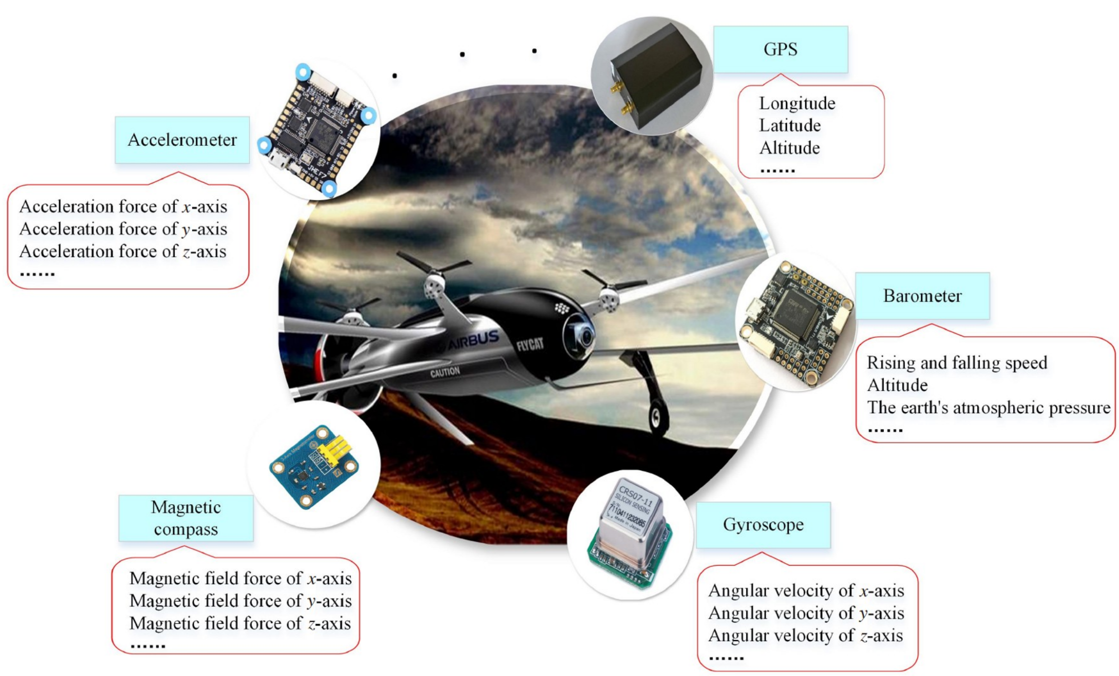


Figure 3 (Color online) UAV flight data are collected by sensors and measuring devices.

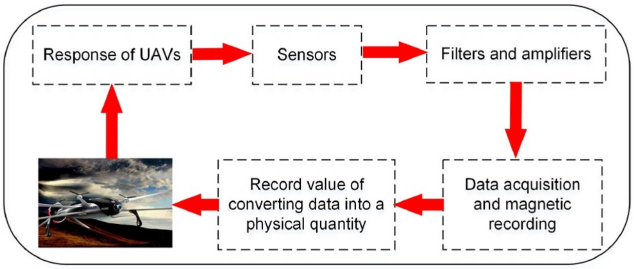


Figure 4 (Color online) UAV flight data acquisition process.

ious parameters, such as position, motion, control, and alarm information, are recorded by QAR. These parameters include longitude, latitude, altitude, wind speed, wind direction, and angle of attack (listed in Table 3).

2.3 UAV real flight datasets

The purpose of UAV flight data anomaly detection involves detecting abnormal flight activities based on flight data. However, abnormal UAV flight data are more difficult to obtain than normal UAV flight data [40]. Hence, most of the research findings on UAV flight data anomaly detection are based on simulation data for verifying and evaluating the proposed methods [33,41,42], which leads to challenges for the practical applications of UAV flight data anomaly detection technologies. To facilitate scholars in verifying the practicability of their methods in a better manner, we will introduce two public UAV flight datasets in this section: ALFA and University of Minnesota UAV real flight datasets [33,43,44].

ALFA datasets were collected and published by Keipour et al. [43] and provide a benchmark for the research of UAV fault detection and anomaly detection. They include many hours of raw data from fully autonomous, autopilot-assisted, and manual flights with tens of anomaly scenarios. To evaluate the methods, the basic facts of the type and time of the anomaly are presented for each scenario. The data types and fault types of ALFA are listed in Tables 4 and 5, respectively.

UAV real flight datasets were collected by the University of Minnesota, including a wide range of flight modes, such as rising, falling, turning, and flying. They are widely used by researchers in anomaly detection research. The datasets were collected from the Thor UAVs at different flight times [45–50]. According to ref. [45], we listed the meanings of some different flight variables of the Thor UAVs (Table 6), which is convenient for scholars to quickly understand the datasets. Table 7 shows the partial public datasets of the Thor UAVs.

As an example of the partial public datasets of the Thor UAVs, the Thor69 dataset contains 75 parameters and represents the 69th flight data of the Thor UAV. Currently, some researchers use its altitude data subsets, such as alt, h, and navalt, to experiment and verify their proposed anomaly detection methods [33].

3 UAV flight data simulation software

Research on UAV flight data anomaly detection is inextricably linked to data, which are essential factors of

Table 2 Advantages of each data collector

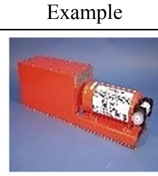
Data collector	Example	Advantages
FDR		(1) Record various states and operating parameters of UAVs; (2) Can better protect parameters and system data; (3) Provide flight conditions and data; (4) Analyze system performance.
QAR		(1) Quick access to raw flight data; (2) Record many flight parameters; (3) Longer recording periods with a higher sampling rate.
MMSC-800, AIFTDS-8000, DAMIEN-VI	–	(1) With a central controller and several powerful external buses; (2) Multiple collectors can be installed on one bus at the same time; (3) Strong data acquisition capabilities and a high degree of flexibility in the equipment.

Table 3 Flight data parameters

Parameter category	Example
Position parameters	Altitude, longitude, latitude, etc.
Motion parameters	East speed, north speed, angular velocity, acceleration, etc.
Operation control parameters	PID parameters, steering gear command, pull rod speed, etc.
Alarm information	"Safe to fly", "attitude mode!", etc.

Table 4 Information about ALFA datasets

Type	Content	Format
Processed	There are 47 autonomous flight data sequences, 7 types of faults, and 23 sudden engine failure scenarios.	.bag, .csv, .mat
Raw	Automated and manual flight data without processing.	.bag
Telemetry	Telemetry data are recorded via NVIDIA TX2 computer in airborne equipment.	.txt
Data flash	The data recorded on the Pixhawk autopilot during the tests.	.txt

Table 5 Fault types in the processed dataset [43]

Fault type	Test cases	Flight time before fault (s)	Flight time w/fault (s)
Engine full power loss	23	2282	362
Rudder stuck to left	1	60	9
Rudder stuck to right	2	107	32
Elevator stuck at zero	2	181	23
Left aileron stuck at zero	3	228	183
Right aileron stuck at zero	4	442	231
Both ailerons stuck at zero	1	66	36
Rudder & aileron at zero	1	116	27
No fault	10	558	–
Total	47	3935	777

Table 6 Description of some variables [45]

Field name	Units	Description
h	M	Barometric altitude above ground (AGL)
alt	m	GPS altitude (WGS84)
navvd	m/s	NAV down velocity
navve	m/s	NAV east velocity
q	rad/s	Y-axis angular rate (pitch)
r	rad/s	Z-axis angular rate (yaw)
hy	Gauss	Y-axis magnetic field
hz	Gauss	Z-axis magnetic field
ax	m/s^2	X-axis acceleration
ay	m/s^2	Y-axis acceleration
navvn	m/s	NAV north velocity
navalt	m	NAV altitude (wGS84)

Table 7 Part of the public datasets of Thor UAVs

Name	Times	Parameters	Public year	Reference
Thor60	60th	93	2014	[45]
Thor69	69th	75	2012	[46]
Thor81	81st	95	2013	[47]
Thor83	83rd	85	2013	[48]
Thor97	97th	84	2013	[49]
Thor98	98th	84	2013	[50]

production [51]. However, it is difficult to develop UAV flight data anomaly detection research due to the high cost of obtaining real flight data. In Section 2.2, we mentioned that most of the current UAV flight data anomaly detection methods are based on simulation data for testing and verifying the effectiveness of the proposed methods. Although there are some differences between simulation data and real data, it is still the main data source for scholars to conduct academic research. Hence, software that generates simulated flight data is an important tool for UAV flight data anomaly detection, such as X-Plane [52], Flight Gear [53,54], Microsoft Flight Simulation (MFS) [55], MATLAB, and V-REP [56], which significantly contributes to the advancement of UAV flight data anomaly detection research. The flight data generated by the software play an important role in evaluating the rationality of flight dynamics model design. Additionally, these simulation data can be used to evaluate the quality of flight simulation training, flight evaluation, and flight trajectory correction. The purpose of this section is to introduce several UAV flight data simulation software, commonly used by scholars, to serve as a reference for researchers to conduct future research on UAV flight data anomaly detection.

Table 8 lists some commonly used softwares that can generate simulated UAV flight data. Although X-Plane and V-Rep can produce accurate and reliable simulation data, they are time-consuming due to low operating efficiency, which can adversely affect real-time anomaly detection and analysis of UAV flight data. Flight Gear and Gazebo can satisfy personal requirements of users although Flight Gear's storage capacity is limited and Gazebo lacks compatibility. This affects the availability and quality requirements of its

Table 8 Information about each simulation software

Name	Advantages	Disadvantages	Open-source
X-plane	(1) Provides aircraft flight parameters output port; (2) Can freely select the required flight parameter data; (3) Provides accurate and reliable simulation data; (4) Easy to operate and has excellent visualization effects.	(1) Slow reaction; (2) Large memory requirements.	No
Flight gear	(1) Realize cross-platform, network communication, and other functions; (2) Convenient for users in secondary development; (3) Satisfies individualized requirements of users.	(1) Complex structure and organization; (2) Difficult to comprehend; (3) Data cannot be automatically stored; (4) Limited amounts of data are recorded.	Yes
MFS	(1) Standardized operations; (2) Easy to operate; (3) Provides Chinese language operation.	(1) Lower operational efficiency; (2) High memory demands; (3) Excess resources due to redundant plug-ins.	No
MATLAB	(1) Can easily use the Simulink library to model, analyze, and simulate various dynamic systems; (2) Provides a graphical interactive environment; (3) Provides powerful functions and an intuitive interface; (4) Strong expansibility and great interaction.	(1) Inefficiency of low-cycle operation; (2) Poor encapsulation.	No
V-REP	(1) Can simulate the entire UAV system or its subsystems; (2) Offers many data interfaces; (3) Variety of programming languages are available; (4) Does not exclusively rely on a mathematical model and aerodynamic parameters; (5) Rapid modeling and verification of aircraft.	(1) High memory demands; (2) Processing and transferring of data are time-consuming; (3) Added script can conflict with the built-in script.	Yes
Gazebo	(1) Realistic 3D environment and high-performance physics engine; (2) Can be used to obtain simulation data and noise with respect to sensors; (3) Satisfies personalized needs of users; (4) Easy to use system operation interface.	(1) Poor compatibility; (2) May not apply to virtual machines or computers with lower configuration.	Yes

simulated UAV flight data. Although MFS is friendly to domestic users in terms of language settings and operations, it is an expensive commercial software with many plug-ins and low efficiency. Comparatively, MATLAB is increasingly preferred as simulation tool for researchers due to its rich functionality, easy user interface, strong extensibility, and good interactivity. However, its computational efficiency and encapsulation necessitate further improvements. Furthermore, softwares, such as Flight Gear, V-REP, and Gazebo, are open-source software, which enables scholars to use them more flexibly for secondary development to satisfy some of their own personalized needs. Furthermore, it is necessary to focus on the security and system reliability of these softwares, which can lead to unnecessary issues.

4 UAV flight data anomaly detection technologies

The purpose of anomaly detection is to identify patterns in data that do not conform to normal behavioral patterns. It is vital to train models using labeled data or by verifying their availability [57]. In recent years, anomaly detection technology exhibits significant advantages in many fields including urban road traffic [58,59], Internet of things [60,61], finance [62,63], and other critical fields.

Anomalies can occur when UAVs display abnormal flight behaviors, sensors, and other abnormal information. These anomalies are then analyzed to predict UAV faults. Given that UAVs are less safe and have a higher failure rate [11,12,64], they result in enormous economic losses to enterprises and departments in practical applications. Thus, research on UAV flight data anomaly detection constitutes a crucial basis for UAV operators to adopt appropriate emergency measures and determine whether UAVs will continue to work [11,33]. However, the challenge translates into designing and developing effective UAV flight data anomaly detection methods. The digital information of UAVs is continuously intensifying, and thus anomaly detection technology is gradually applied to UAV flight data. In extant studies, advanced anomaly detection methods were proposed that can be broadly categorized into three categories: knowledge-based, model-based, and data-driven [11]. In this section, we provide a more comprehensive analysis and summary of the three categories.

4.1 Knowledge-based methods

Knowledge is a systematic and concise understanding obtained by human beings in various ways. Hence, it is the sum of the results of human beings exploring the material world, studying the spiritual world, and understanding the objective world (including humans themselves) in practice such as the description of facts and information or skills acquired in education and practice. Knowledge-based methods can fully utilize prior knowledge and expert experience and are widely used in recommendation systems [65], biomedicine [66], smart city [67], and other fields. For UAV flight data anomaly detection, methods can be used to detect flight data anomalies by summarizing expert experience and knowledge in the specific field of UAVs. Subsequently, it is necessary to design and develop corresponding anomaly detection algorithms to detect different types of anomalies in UAV flight data without accurately modeling UAVs. As shown in Figure 5, the flight data (including telemetry data, altitude, and data flash) are first combined with the UAV's specific knowledge or expert experience to establish flight data anomaly types for UAVs such as point anomalies, context anomalies, and collective anomalies. Based on different abnormal UAV flight modes, it is then possible to design anomaly detection algorithms to realize anomaly detection. The algorithms include adaptive threshold neural-network, PF, and FIS [68,69].

There is a paucity of studies on knowledge-based methods in the field of UAV flight data anomaly detection due to their defects such as high dependence on prior knowledge, expert experience, models, and rules. Although the methods do not require accurate UAV models, it is challenging to transfer them from one application to another. Additionally, it is challenging to expand their use to various types of anomalies. As listed in Table 9, the method proposed in a previous study [69] offers high anomaly detection accuracy and early anomaly prediction. However, the large calculation of the PF and poor performance of the FIS limit its ability to detect anomalies in terms of false-positive rate and processing, and thus it is unable to detect the impact of unknown anomalies. Although sparse modeling and T-Digest can capture instantaneous anomalies and address complex correlation between sensors, T-Digest only focuses on instantaneous events and does not filter over time [70]. This can lead to more false positives and affect the performance of anomaly detection. Furthermore, adaptive threshold neural-network and clustering algorithms are significantly dependent on the knowledge of experts in specific fields [68,71], which also poses challenges to their practical application. Although these methods exhibit certain limitations, they can also satisfy the accuracy of UAV anomaly detection to a certain extent and decrease the time cost of anomaly identification [70,71], which provides a reference for research in UAV flight data anomaly detection. Additionally, when the threshold is fixed, the performance of the UAV anomaly detection algorithm can be guaranteed [68].

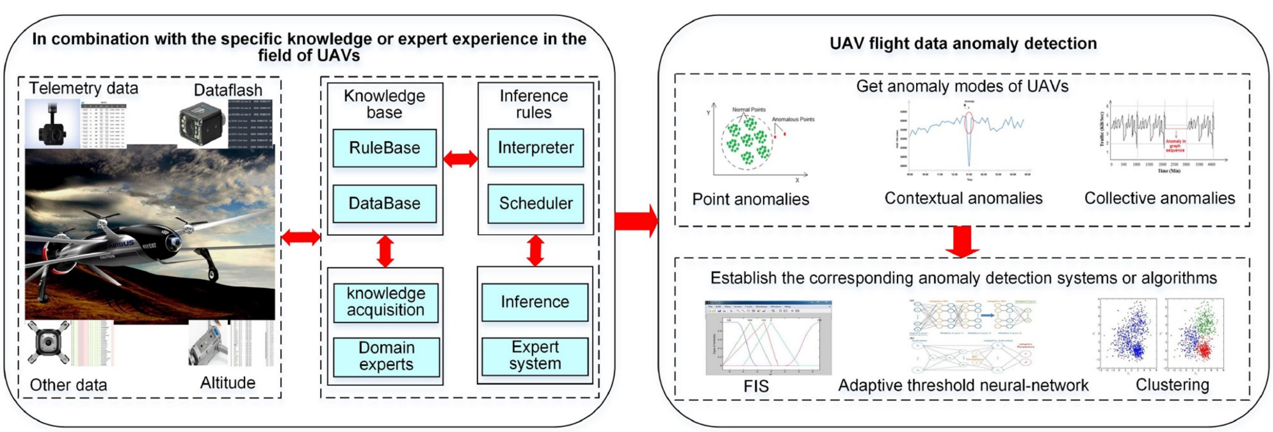


Figure 5 (Color online) The general flow of knowledge-based anomaly detection methods for UAV flight data.

Table 9 Knowledge-based anomaly detection methods for UAV flight data

Authors	Data	Methods	Benchmarks	Software	Advantages
Qi et al. [68]	Acceleration, position, angular velocity, etc.	Adaptive threshold neural-network	Neural-network	–	Can eliminate the requirement for changes in the threshold based on changes in flight conditions and can significantly enhance the performance of fixed threshold algorithms.
Bu et al. [69]	Flight data information related to navigation sensors	PF + FIS	–	MATLAB	High level of anomaly detection accuracy and ability to predict anomalies at an early stage.
Radke et al. [70]	Angular displacement, acceleration, angular velocity, etc.	Sparse modeling + T-Digest	*K*-means	–	Can capture transient anomalies, handle complex correlations between sensors, and provide clear alarm trigger points that indicate faults.
Schmidt et al. [71]	Log of CPS	Clustering algorithm	–	–	Significantly decrease time and effort required by experts to identify anomalous events in logs.

4.2 Model-based methods

Essentially, models constitute artificial simulations or abstractions based on certain features and relationships that exist in the objective world. Specifically, models correspond to the forms and structures of objects and explain their relation to each other through words, charts, formulae, computer programs, or other mechanisms. They can be used to objectively test models and analyze practical problems. Therefore, these methods are used in UAV flight data anomaly detection research to overcome the challenges and cost of abnormal UAV flight data acquisition, and realize high anomaly detection performance. Furthermore, these methods can provide detailed and interpretable anomaly information when an accurate physical model of the UAV system is obtained. As shown in Figure 6, the general flow of the methods involves establishing the corresponding physical models for UAVs or their subsystems by combining expert domain knowledge. Secondly, it is necessary to construct the observer system models. The residuals are then calculated by comparing the estimated value with the actual value to detect anomalies in UAV flight data. Furthermore, research on model-based UAV flight data anomaly detection methods has been developed in recent years (Table 10).

Model-based methods exhibit advantages of simplicity, economy, and speed of operation. To obtain better anomaly detection performance, the methods should combine UAV's domain knowledge or system mechanisms to establish accurate UAV physical models. The reality is that it is difficult to model accurate physical models of UAV's every subsystem. Moreover, few abnormal samples of real UAV flight data exist in most cases, and thus their applicability and superiority is accurately observed only when the abnormal modes of UAVs are known. Hence, the methods exhibit certain limitations. Based on Table 10, although EKF displays evident advantages in terms of computing cost, there are no fault-tolerant strategies [72]. The methods in previous studies [73,76,77] can be applied to nonlinear models al-

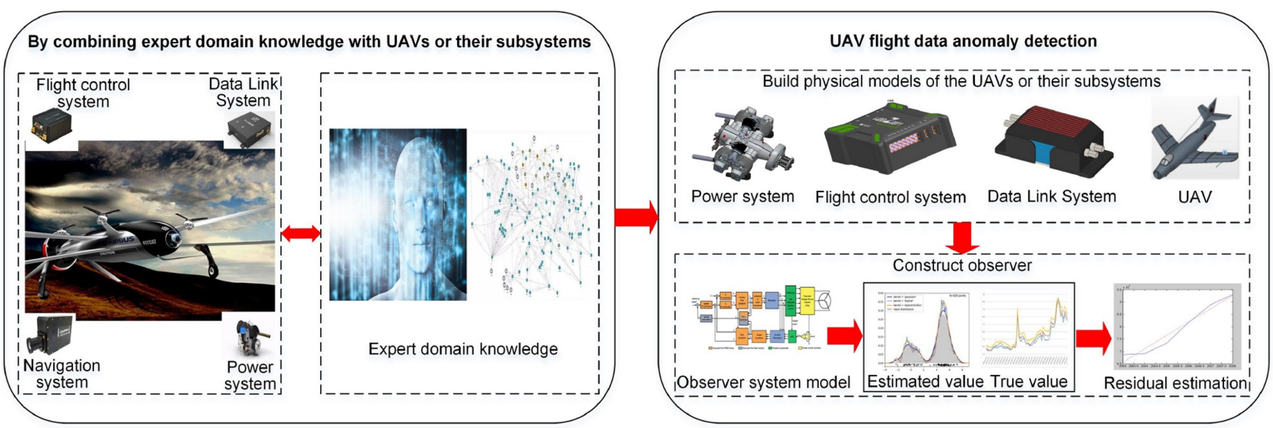


Figure 6 (Color online) The general flow of model-based anomaly detection methods for UAV flight data.

Table 10 Model-based anomaly detection methods for UAV flight data

Authors	Data	Methods	Benchmarks	Software	Advantages
Abbaspour et al. [72]	Parameters related to rudder, elevator, aileron deflection, etc.	EKF	RNN	MATLAB	Can satisfy real-time application needs and provide high security and reliability and quick computing time.
López-Estrada et al. [73]	Position, velocity, angular velocity, etc.	LPV	–	MATLAB	Can accurately represent nonlinear model and independently design the observer.
Suarez et al. [74]	Information about position, visual sensors, etc.	Vision-based FDIR system	–	–	Can guide UAVs with faulty sensors to safe states.
Wang et al. [75]	Acceleration, angular velocity, etc.	A novel sparse optimization technique	Traditional model-based anomaly detection	MATLAB	Can accurately detect anomalies.
Wang et al. [76]	Acceleration, velocity, dynamic pressure, etc.	LSM + Bias compensated terms	Anomaly detector based on residual	–	Can transform the problem of anomaly detection of multiple UAV formations into a nonlinear system identification problem.
Zhang [77]	Airspeed, angle of attack, pitch angle, pitch rate, etc.	DUKF	–	MATLAB	Can separate state estimation and parameter estimation and can be directly applied to nonlinear models.
Guo et al. [78]	University of Minnesota UAVs real flight datasets	EKF + Ensemble algorithm	–	–	Exhibits good anomaly detection performance and displays a certain practical value.

though the accuracy of parameter estimation directly affects the performance of the designed anomaly detector [76]. However, separating state estimation and parameter estimation [77] or independently designing the observer [73] leads to more obvious advantages in UAV flight data anomaly detection. Additionally, the methods in previous studies [74,75] also rely on expert knowledge. Conversely, the method proposed by Guo et al. [78] exhibits more advantages in terms of performance and practicability although its computation cost should be further reduced.

4.3 Data-driven methods

Data-driven corresponds to data-centric methods for establishing the correlation relationship between their internal characteristics to make decisions and actions as follows: (1) collect considerable data using various softwares; (2) organize data to form information, which is then integrated and refined; (3) an automatic decision model is formed after training and fitting data. The potential value of data was further improved with the rapid development of big data technology [79], cloud computing technology [80,81], and artificial intelligence algorithms [82,83]. The exponential growth of data has also spawned many new domain terms such as agricultural big data, industrial big data, and medical big data [84–86]. Hence, the technologies led to many data-driven methods [87,88], which significantly promoted the development of various fields. Therefore, when compared with knowledge-based and model-based methods, data-driven methods constitute a research hotspot in the field of UAV flight data anomaly detection.

As shown in Figure 7, UAV flight data, including altitude, telemetry data, and data flash, are acquired by sensors and are considered as the source of analysis of UAV system behaviors. Subsequently, abnormal UAV flight data are identified and marked via data-driven algorithms. When compared with model-based methods, data-driven methods do not require complex modeling of the physical characteristics of UAV systems and can maximize the use of the information contained in sensor data. Additionally, accurate anomaly information can be detected via various data-driven methods based on the modified characteristics of the flight data information to ensure the safety and stability of UAVs. Data-driven methods are widely applied to the anomaly detection of key parts and systems of UAVs. Table 11 lists recent studies on data-driven methods for UAV flight data anomaly detection.

Internal dynamics of UAVs is not necessary to understand in detail for data-driven anomaly detection methods. The available flight data can be considered as a source of information with respect to the UAV systems' behaviors. Although the methods are based on statistical information to detect abnormal data, they display high flexibility without model analysis. In Table 11, PCA [89], ANFIS [74], and mGMM [96] exhibit evident advantages and effects in terms of detection accuracy, algorithm robustness, and real-time anomaly detection. Furthermore, the methods proposed in extant studies, refs. [90] and [93], can also decrease the cost of data labeling [90] and false alarm rate of anomaly detection [93]. However, defects still persist. For example, in a previous study [90], the method performance is dependent on sampling strategy where the assumption of improving S3VM is unrealistic. Additionally, the model involves a long training cycle. Although the method in previous work [91] performs well in terms of anomaly detection time and robustness of the algorithm, the performance of their method requires further improvement such as improving the accuracy and decreasing the false alarm rate. Wang et al. [94] used the Pearson correlation coefficient (PCC) to extract correlation parameters as experimental data. However, PCC only measures linear correlation present in the flight data. Given the complex linear and nonlinear correlations in the UAV flight data, nonlinear correlation parameters should be further considered in future studies. The method proposed in a previous work [97] can cope with small deviations from the expected sampling time and exhibits good robustness and

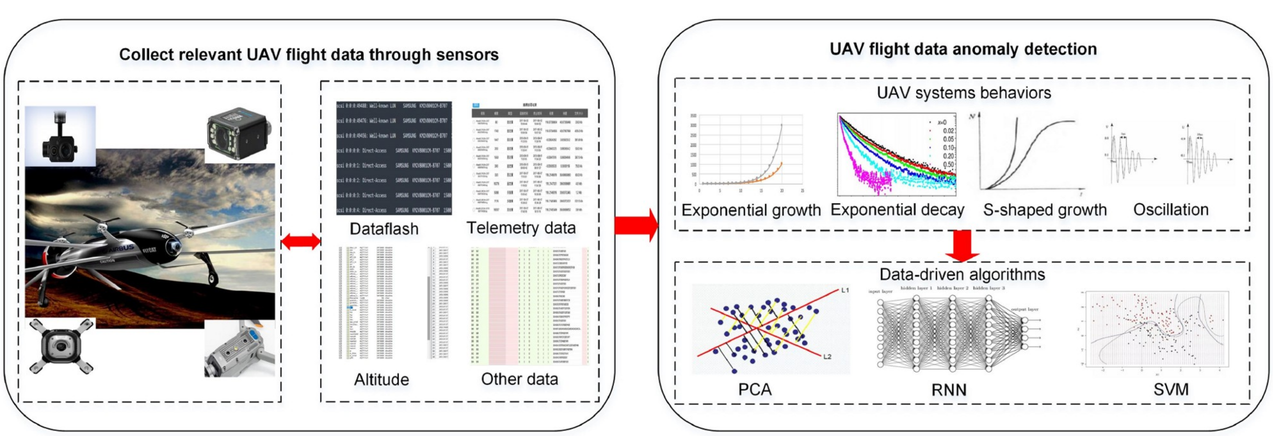


Figure 7 (Color online) The general flow of data-driven methods for UAV flight data anomaly detection.

Table 11 Data-driven anomaly detection methods for UAV flight data

Authors	Data	Methods	Benchmarks	Software	Advantages
Alos et al. [89]	Longitude, latitude, altitude, etc.	PCA	MKAD	–	Fewer training datasets and higher detection accuracy.
Wang et al. [11]	North speed, pneumatic lifting speed, etc.	LSTM	–	–	Strong approximation ability to complex functions and evident advantages to address time series anomalies and automatic feature extraction.
Pan et al. [90]	Telemetry data	MS + S3VM	SVM + S3VM	–	Decreases labeling costs and improves the performance of the anomaly classification model.
Sun et al. [91]	Climb, horizontal flight, descent parameters, etc.	ANFIS	PF + FIS	MATLAB	Can quickly and accurately realize anomaly detection of UAV flight data with strong robustness of its algorithm.
Titouna et al. [92]	ALFA	KLD + ANN	–	MATLAB	Exhibits high accuracy for anomaly detection and use of spatial and temporal correlations in the sensors' data to realize online detection.
Pan [93]	Simulated flight data + University of Minnesota UAVs real flight datasets	PAA + SVDD + KPCA	SVDD + KPCA	Flight Gear	Excellent anomaly detection performance, lower false positive rate, and valuable practicability.
Wang et al. [94]	Latitude, longitude, altitude, etc.	MRM	–	–	Excellent adaptability and anomaly detection performance.
Duan et al. [95]	Remote sensing data	RVM	–	Flight Gear	Simple and easy to operate.
Li et al. [96]	Acceleration, rudder position degrees, ailerons, etc.	mGMM	–	MATLAB + X-Plane	High detection sensitivity, calculation efficiency, and lower calculation cost and can realize real-time monitoring.
Bronz et al. [97]	Flight test log	SVM	–	–	Strong robustness and higher accuracy, and a solution on a small deviation from the expected sampling time.
Bae et al. [98]	Status information, position information, speed information, etc.	LSTM-AE + AE	–	–	Does not require a high number of calculations, can effectively reduce the anomaly detection time, and satisfy the demand for anomaly detection in the UAV environment.
Bell et al. [99]	ALFA	Stacked LSTM-AE	statistic thresholding and without the dynamic thresholding	–	Decreases latency of true anomalous behavior detection and can be easily applied to aircraft data from vehicles with different characteristics.
Aksoy et al. [100]	Trajectory data	GAN	–	–	Contextual anomalies in the sequential data are successfully detected.

high accuracy. However, the over-fitting problem due to the limited training data samples of this method limits the model's generalization ability. Bae et al. [98] and Bell et al. [99] used the LSTM-AE approach for UAV flight data anomaly detection. Although their methods effectively decrease anomaly detection time, severe dimensionality reduction leads to the risk of high reconstruction loss using a single AE [98]. In contrast, stacked AEs enable the model to reduce dimensionality gradually. This in turn smooths the slope and retains more relevant information in the low-dimensional space [99]. Conversely, GAN exhibits a larger window to observe pattern anomalies and can detect abnormal patterns that cannot be detected by AE [100].

5 Applications

In recent years, the development of UAV anomaly detection technology has prompted domestic and international institutions to develop many platforms and frameworks that can be used for UAV anomaly detection. Simultaneously, domestic and foreign research institutions have also performed considerable applied research in UAV anomaly detection, which has further promoted the application process of theoretical research. To this end, in this section, we provide a more comprehensive analysis and summary of the platforms and frameworks and related studies performed by the institutions in this field.

5.1 Platforms and frameworks

Anomaly detection technologies and applications gradually matured following many years of development [101–103]. Several platforms and frameworks emerged for detecting UAV flight data anomalies including, rt-R2U2 [104], Ardupilot [105], embedded intelligent system (EIS) of UAVs [106], and an online and noninvasive embedded anomaly detection system (ONEADS) [107]. This significantly promoted the application of UAV flight data anomaly detection. Table 12 provides a summary of the advantages and disadvantages of each platform and framework.

With respect to current platforms and frameworks, rt-R2U2 can perform real-time monitoring although its framework includes high hardware requirements and relies on prior knowledge, thereby increasing the cost of anomaly detection to some extent and reducing the performance of anomaly detection. Similarly, while Ardupilot supports a variety of UAV models, its code is redundant and cannot detect or diagnose more complex abnormal modes. Therefore, its performance is limited in practical applications. Comparatively, EIS and ONEADS include numerous algorithms for anomaly detection and display the capability of parallel data processing, which significantly improves computational efficiency. Furthermore, they can satisfy real-time anomaly detection requirements. Nevertheless, their computing cost, hardware requirements, and system complexity should be further reduced and optimized.

5.2 Application status

UAVs are ideal for military and civilian fields due to their significant environmental adaptability, high degree of autonomy, zero casualties, and long-term operability [108–110]. Almost every country in the world has evidenced a keen interest in UAVs. As the base of scientific research, universities play a vital role in the process of scientific research. Currently, when compared with other research institutions, universities lead research in abnormal detection of UAV flight data. In addition to universities, research institutes and enterprises related to UAVs also significantly contribute to the field of UAV flight data anomaly detection. Therefore, to comprehensively analyze the current application status of UAV flight data anomaly detection, we first discuss representative domestic and foreign universities and some of their research results in UAV flight data anomaly detection and briefly analyze their application research results. Second, we summarize related work of some domestic and international UAV flight data anomaly detection research institutions except universities.

Table 13 provides a list of references of universities in China and abroad involved in the application of UAV flight data anomaly detection technology. Domestic research includes studies by He et al. [33,41,111,112] of the Harbin Institute of Technology. They designed and developed UAV anomaly detection technology based on OSPABP, subspace learning, and subspace matrix. The effectiveness of the methods is verified based on simulated and real UAV flight data, and computational and storage complexity of the algorithms can satisfy airborne processing requirements. Pei [113] from the University of Electronic Science and Technology designed a set of comprehensive analysis software that can detect UAV flight data anomalies. The key concept involves using expert systems to detect abnormal flight data, which can provide a scientific and effective basis for UAV fault detection and maintenance. Liu et al. [16] from the Beihang University proposed a method to detect UAV flight data anomalies in real-time. They used KNN to provide reasonable prediction values for different flight data anomaly types, which can be easily applied to airborne systems and provide real-time data preprocessing for other aviation systems and ground control systems. Furthermore, international researchers, including Keipour et al. [43] from Carnegie Mellon University and Taylor [45–50] from University of Minnesota in America, Alos et al. [89] from University of Damascus (Syria), Bae et al. [98] from Hanyang University (Korea), White et al. [114] from University of Glasgow (United Kingdom), and Titouna et al. [92] from University of Paris (France), have also significantly contributed to applications of UAV flight data anomaly detection. They disclosed UAV flight data anomaly detection datasets [45–50] and provided real-time online UAV flight data anomaly detection methods [45–50,92,114].

Table 12 Advantages and disadvantages of each platform and framework

Name	Advantages	Disadvantages
rt-R2U2	(1) Detect faults and violations of safety or performance rules; (2) Analyze and preprocess signals from sensors and software; (3) Can detect fault anomalies in real-time.	Restricted by hardware, dependent on prior knowledge, and can only be executed via a plug-and-play architecture.
ArduPilot	(1) Support multiple ground stations for flight planning and flight control; (2) Simple and friendly user interface; (3) Simulate flight of fixed-wing aircraft, multirotor aircraft, and other types of aircrafts.	Sensor data analysis tool is limited to specific sensor data and cannot diagnose or detect complex faults.
EIS	(1) Capable of receiving real-time flight data; (2) Realize online anomaly detection for key sensors and components; (3) Support acceleration of multiple algorithms.	High hardware requirements and high complexity of the system.
ONEADS	(1) Include a high-speed, parallel, dynamic, and non-deterministic computation; (2) Include algorithms for detecting anomalies; (3) Satisfy requirements for UAV flight data anomaly detection in real-time.	With a significant amount of computation, a more complex algorithm model, and significantly higher requirements for hardware and software.

Table 13 Part of UAV flight data anomaly detection applications research literature of universities

Authors	Methods	Effects	University	Nation
He et al. [41]	OSPABP	Improve detection accuracy and decrease false alarms rate.	Harbin Institute of Technology	China
Chen [27]	LS-SVM + *K*-means	With real-time anomaly detection, high performance, and low power consumption.	Harbin Institute of Technology	China
He [111]	Subspace learning	High detection accuracy, low false detection rate, and high calculation efficiency.	Harbin Institute of Technology	China
He et al. [33]	Subspace matrix	Low data recovery error rate and high accuracy of anomaly detection.	Harbin Institute of Technology	China
Pei [113]	Rule-based forward reasoning method	Can assist UAVs in detecting faults and improving their efficiency.	University of Electronic Science and Technology	China
Wang et al. [11]	LSTM	Strong data recovery capability and excellent anomaly detection performance.	Harbin Institute of Technology	China
He et al. [112]	SSSLAD	High accuracy and rapid identification of anomalous sources of flight data.	Harbin Institute of Technology	China
Liu et al. [16]	KNNS	More efficient and accurate than traditional methods of real-time anomaly detection.	Beihang University	China
Keipour et al. [43]	–	Dataset of publicly available real flight data for fault detection, isolation, and anomaly detection.	Carnegie Mellon University	America
Taylor [45–50]	–	Datasets for Thor UAVs during different flight regimes for anomaly detection were made public.	University of Minnesota	America
Alos et al. [89]	PCA	Without flight anomaly false alarms and training mass data.	University of Damascus	Syria
Bae et al. [98]	LSTM-AE + AE	Can effectively reduce anomaly detection time.	Hanyang University	Korea
White et al. [114]	SDN + NFV	Can be modified to cater to specific UAV types and provide operators with real-time and mobile deployment capabilities.	University of Glasgow	United Kingdom
Titouna et al. [92]	KLD + ANN	High accuracy is realized in anomaly detection, and the spatial and temporal correlation of sensor data can be used to realize online anomaly detection.	University of Paris	France

However, in general, there is a paucity of research on UAV flight data anomaly detection in universities in China and abroad. Most research findings remain in the theoretical phase. Although the aforementioned authors claim that their methods can realize positive results, there is a lack of practical engineering application verification. Given that many uncertain factors exist in the practical application process, the effectiveness of these methods should be further verified.

The authors recently conducted studies on UAV flight data anomaly detection and purchased UAV ground control stations and different types of UAVs. The UAV is equipped with multiple data collectors to collect different types of flight data and transmit flight data to the UAV ground control station in time. Additionally, the UAV ground control station also exhibits data interfaces for exporting flight data. The simulated flight data can also be obtained via the UAV model built-in in the UAV ground control station, and the faults can be injected manually, which provides anomaly data sources for better research on anomaly detection of UAV flight data.

With the exception of the aforementioned universities, NASA developed a UAV health management framework rt-R2U2 based on swift UAV [104]. We introduced its advantages and disadvantages in Section 5.1 and will not detail the same here. The specific process of rt-R2U2 includes the following stages: (1) non-intrusion access to the UAV hardware architecture; (2) obtain flight data from the existing UAV airborne data bus; (3) monitor abnormal state of key components, flight control software, and flight behavior via built-in online anomaly detection algorithms; (4) the detection results are fed back to the flight control processor via the airborne data bus, which is convenient for flight control emergency handling. Industrial departments, including China Aerospace Science and Industry Group, Beijing Institute of Spacecraft Environment Engineering, Beijing Aerospace Unmanned Vehicles System Engineering Research Institute, and Centre for Transport Studies of Imperial College London, examined the application of UAV flight data anomaly detection technology [11,41,91,94,115]. Additionally, many enterprises recently actively performed research on UAV flight data anomaly detection. Based on the characteristics of UAV sensor data, Duan et al. [116] from the Xi'an ASN Technology Group Co., Ltd., China, proposed an anomaly detection method based on KPCA to overcome high dimensionality and nonlinearity of UAV flight data. The flight data generated by Flight Gear verified that the method realizes satisfactory anomaly detection performance.

6 Future directions

It is established that UAV flight data anomaly detection has significantly advanced in terms of technologies and applications over the last few years. However, given that research in this field commenced recently, many important issues persist and require resolution. In this section, we analyze and summarize the future research directions and challenges of UAV flight data anomaly detection based on the content described in Sections 3–5 (Figure 8).

6.1 Developing simple and understandable simulation software

It should be noted that although many UAV flight data simulation generation softwares currently exist, most of them involve complex operations and are not available in languages that are friendly to domestic users (such as Flight Gear and Gazebo). Given the difficulty in obtaining real UAV flight data, UAV flight data simulation software remains an essential tool for researchers in the present and future. Hence, development of software with an emphasis on simple operation and Chinese language is an effective way to accelerate domestic research in UAV flight data anomaly detection. It also serves as a reference direction for future research.

6.2 Improving the interpretability of models

Interpretability is the ability to help people understand or explain [117,118]. Although model-based UAV flight data anomaly detection methods can realize high detection performance, their interpretability relies on accurate physical models of UAV systems. Hence, it is difficult for researchers to combine data, models, and problem understanding, and thus, it is impossible to locate or track anomalies in UAV flight data. Thus, interpretable models can be developed, or interpretable methods can be used to analyze the models after modeling. Additionally, we can also utilize LIME [119], model substitution [120], and other technologies to enhance the interpretability and traceability of abnormal information from the perspective of local and global models, which constitutes the main research direction for future research.

6.3 Exploring new data-driven algorithms

Data-driven methods are based on the data information extracted from the historical flight data without modeling the accurate physical models of UAVs [11,89,90]. Although we described many advantages of data-driven UAV anomaly detection methods in Section 4.3, their limitation is that UAV flight data corresponds to time series data that are spatially and temporally correlated. However, most previous methods only consider spatial correlation of multi-dimensional flight parameters or temporal correlation of a single flight parameter. Additionally, the real UAV flight data contain random noise that is not considered by scholars in their model analysis. This also poses a challenge to the applicability of the proposed methods [18,96,121]. Thus, in the future, it is necessary to weigh the spatio-temporal correlation of UAV flight data and reduce its random noise, which corresponds to a key research direction of studying new data-driven methods for detecting UAV flight data anomalies. In addition to the difficulty of algorithm innovation, the practicality and scalability of algorithms are also important topics that should be explored in future research.

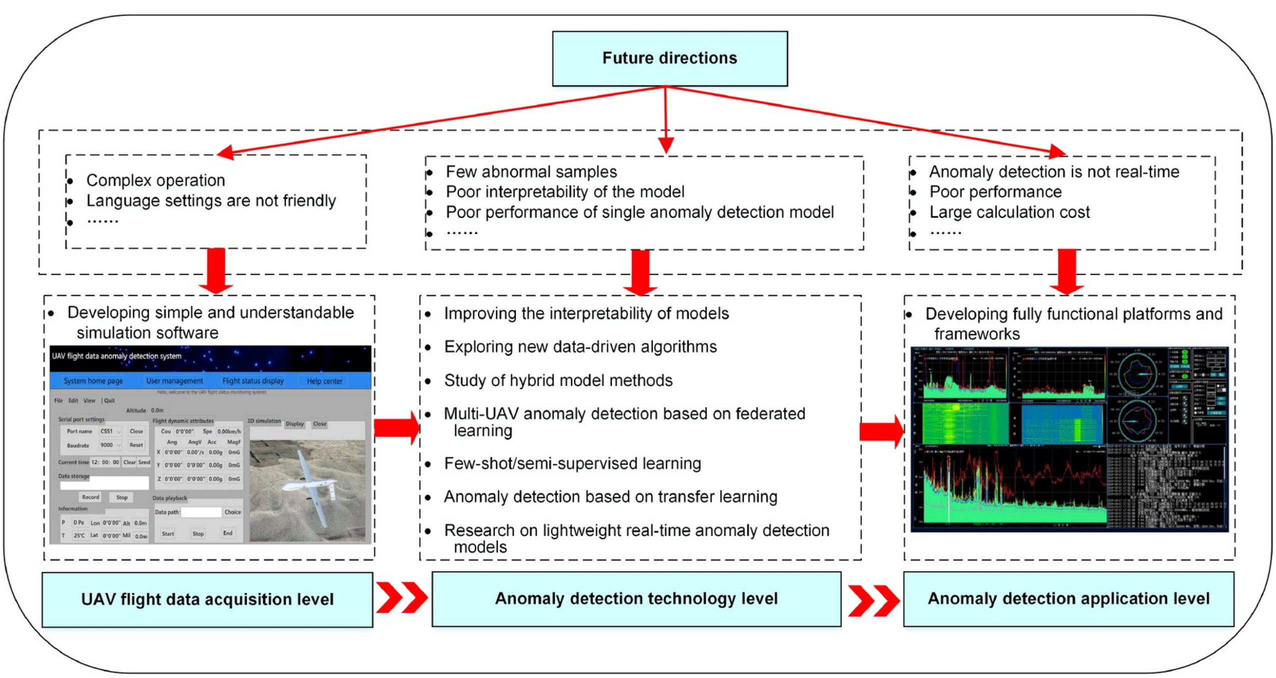


Figure 8 (Color online) Structure diagram of future research directions.

6.4 Study of hybrid models

Expert knowledge and experience can be used to detect anomalies using knowledge-based anomaly detection methods. However, they are highly dependent on prior knowledge, which results in poor anomaly detection ability. Model-based anomaly detection methods for UAV flight data construct an observer by establishing accurate system physical models to obtain high anomaly detection performance. Nevertheless, the difficulty in establishing accurate physical models of UAVs limits their applications to a certain extent. However, they exert a significantly positive effect on anomaly detection performance when obtaining precise physical models of UAVs. Additionally, although data-driven anomaly detection methods are not dependent on prior structure information and avoid the difficulty of creating physical models of UAVs, they are considerably affected by training data, thereby resulting in high false–positive rates [19]. It is possible to combine the advantages and disadvantages of the aforementioned methods to build hybrid models for improving generalization and practicability of models. Given the limitations of the aforementioned methods, researchers also face a major challenge in ensuring the feasibility and effectiveness of hybrid models.

6.5 Multi-UAV anomaly detection based on federated learning

Majority of the current knowledge-based, model-based, and data-driven anomaly detection methods for UAV flight data are limited to the detection of anomalies in a single UAV. However, the increase in UAV cluster anomaly detection [122,123] research poses a challenge to data transmission, calculation, and storage in computers. New technologies are urgently required to overcome this bottleneck. Hence, federated learning is considered as a solution. It is a new distributed machine learning paradigm driven by multi-party data participation and maximizing data value through encrypted interaction [124–126]. It can be used to train models without transmitting the local flight data of a single UAV. This allows the central server to significantly reduce the calculation and storage costs of analyzing multi-dimensional UAV flight data. Although its effectiveness has not been verified, it necessitates further investigation.

6.6 Few-shot/semi-supervised learning

It is not feasible to obtain significant real abnormal UAV flight data for data anomaly detection tasks. Most abnormal data are obtained via simulation software. Hence, few-shot learning methods [127–129] can be used to train the model by using many normal UAV flight data and small abnormal ones to enhance its anomaly detection performance. Furthermore, the UAV flight data anomaly detection tasks are categorized as unsupervised model training, and thus it is difficult to determine whether or not samples are normal. This is a factor that adversely affects the performance of the model. Thus, the semi-supervised learning method [130–132] can be used to label abnormal and normal flight data to improve the performance of anomaly detection. However, collected anomaly samples are also characterized by incomplete categories. Hence, an area of future research involves ensuring the generalizability and scalability of the models.

6.7 Anomaly detection based on transfer learning

Existing UAV flight data anomaly detection algorithms focus on specific flight level anomaly detection or instantaneous anomaly detection tasks. When the task changes, the model should be rebuilt from scratch. Additionally, supervised learning methods lead to strict requirements on the number of data samples, uniformity of data distribution, and completeness of labels [133]. Therefore, a challenge in UAV flight data anomaly detection model research involves quickly modeling new data based on simulated data and existing algorithmic models. The aim of transfer learning involves transferring knowledge from existing models and data to the target to be learned via exploiting correlation between the learning target and existing knowledge. It is widely used in fault diagnosis and can cope with problems such as task variation [134], insufficient samples, and incomplete labels [135,136]. Hence, transfer learning-based methods can be employed to decrease the number of training data samples and training time required for the target domain model [137] in UAV flight data anomaly detection. Methods, including convolutional neural network (CNN) [138,139], can be used to simply tune parameters to provide unified, end-to-end solutions for different flight data anomaly detection tasks. However, with respect to flight data, issues including what to transfer, how to transfer, and existence of negative transfer and transfer boundaries should be further examined and explored.

6.8 Research on lightweight real-time anomaly detection models

Most current UAV flight data anomaly detection algorithms are offline and do not satisfy UAV real-time anomaly detection requirements. Real-time anomaly detection of flight data during UAV flight is necessary to monitor whether anomalies occur during UAV flight in real-time for ensuring safe and reliable operation of UAVs [140]. Additionally, the actual deployment of the UAV flight data anomaly detection algorithm is inseparable from the computing platform as a carrier. When the complexity of the model increases, it results in higher requirement of computational resources. It is a significant challenge to satisfy computational and accuracy requirements of real-time flight data processing with limited computational resources and energy consumption. Therefore, the focus of current research involves designing lightweight real-time anomaly detection algorithms with low model complexity.

6.9 Developing fully functional platforms and frameworks

For the aforementioned UAV flight data anomaly detection platforms and frameworks, rt-R2U2 is dependent on prior knowledge and exhibits high hardware requirements. Ardupilot's code is redundant and not user-friendly and EIS and EADS exhibit high calculation costs. These issues present challenges to the performance and practicality of UAV flight data anomaly detection. Although they exhibit certain limitations, a research direction in the future can be utilized by using their complementary advantages for developing application platforms and frameworks that are optimized and efficient.

7 Conclusions

The role of UAVs in various fields is more evident and important, and thus the safety of their operations has also received unprecedented attention. To ensure the safe flight of UAVs, it is crucial to detect anomalies in-flight data. Specifically, the study focuses on the following four aspects.

(1) Data constitutes the foundation for anomaly detection in UAV flight data. Currently, most researchers focus on simulated flight data and publicly available flight datasets. Therefore, we briefly introduced and explained some public datasets used for UAV flight data anomaly detection. We also introduced simulation software that can obtain simulated UAV flight data including their advantages and disadvantages. The aim of the study involves aiding in the selection of relevant public datasets or simulation software to obtain UAV flight data to improve the performance of UAV anomaly detection research.

(2) Based on the content (1), we conduct a more comprehensive comparison and analysis of UAV flight data anomaly detection technology. The advantages and disadvantages of knowledge-based, model-based, and data-driven methods in the field of UAV flight data anomaly detection are highlighted. In terms of extant literature, extant studies focus on data-driven methods as opposed to knowledge-based and model-based methods. This is attributed to the rapid development of big data technology and artificial intelligence algorithms in recent years, which provides strong technical support for data analysis.

(3) To comprehensively analyze the current application status of UAV flight data anomaly detection in China and abroad, we briefly expounded the following three aspects: universities, research institutes, and enterprises. Among them, universities focus on the field of UAV flight data anomaly detection, and most technologies involved in their research results correspond to data-driven methods, which is consistent with the current development trend of UAV flight data anomaly detection technology described in the content (2). However, systematic research on the same is not conducted by UAV flight data anomaly detection research institutions including universities. Currently, there is no systematic technical system for UAV flight data anomaly detection, and most of the research results are still in the theoretical research stage.

(4) Based on the contents (1)–(3), we provide some directions for future research and specific implementation details to provide references for subsequent research scholars.

Evidently, existing UAV flight data anomaly detection technologies and applications have realized satisfactory results. However, given the characteristics of multi-dimensionality, low rank, data flow, and relatively weak anomaly detection technology of UAV flight data, the development of UAV flight data anomaly detection has been hindered to a certain extent. Therefore, it is necessary to study the anomaly detection of UAV flight data in the future.

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