REVIEW ARTICLE

Advancement in Fault Detection of Internal UAV Damage

Lê N. Sơn

International High School of Ho Chi Minh City, 1 Xuân Thủy Rd, Thủ Đức, HCMC 70000, VN; lenamson2008@gmail.com

ABSTRACT: As UAVs become increasingly popular in both military and civilian applications, more sophisticated technologies related to UAVs are being developed to meet these demands. However, as technology becomes more complex, faults will become more common. This paper aims to examine the recent development of technology that enables companies to detect faults in UAVs before or during deployment, thereby avoiding potential problems in the future. Initially, more traditional methods were used to detect these problems early, such as model-based solutions that included internal sensors for sound, frequency, and signal response time between components. Due to recent developments in AI, more experimental data-driven models are emerging in response to the growing demand for AI; consequently, AI-driven solutions have become increasingly common. This review paper aims to connect different STEM fields to efficiently solve the problem of fault detection and suggest a more affordable method for detecting potential critical faults that may cause significant damage to the UAV.

KEYWORDS: Engineering, UAV, Drones, Fault detection, Artificial Intelligence.

Introduction

Unmanned Aerial Vehicles or (UAVs) have become popular in both military and civilian applications, from overseas reconnaissance, cargo delivery, to agriculture development and environmental monitoring, Novel technologies are being developed to meet the growing demands, which have not been effectively tested enough therefore having a higher risk of internal and external damage from preventable malfunctions which pose a threat to operation and budget to the users.[1]

Fault detection within UAVs is achieved by identifying anomalies or failures in the vehicle's components, usually vital functions such as propellers, sensors, actuators, and structural elements, before they escalate into potential problems. Early empirical papers heavily relied on a data-driven model, which compares real-time sensor data to the expected data set of a UAV.[2]

Although these methods allow for a basic framework to detect basic faults, they lack the adaptability to the dynamic situation or environmental disturbances that come with real-life usage. However, this problem has been identified and has been researched to find a solution. This solution is eventually referred to as Data-Driven or Machine Learning Methods.[3] This solution uses neural networks to use multiple different sensors and data sets on board the UAV to help capture and assess abnormalities and better detect faults, which include vibration, acoustic signals, flight trajectory, and motor data, to cross-reference different data sets of faults better and detect fault signatures with higher accuracy.[3]

The paper aims to report on the current technological advancements in UAV damage detection. Integrating data-driven AI models with traditional early detection methods can significantly reduce the likelihood of UAV crashes. Early fault detectors employ model-based methods to detect abnormalities in the critical components of a UAV.[2] Authors Altinors, Ayhan, and Ghazali, Mohamad, use vibration sensors and acoustic signatures to test the effectiveness of such sensors on abnormal/damaged motors.[4,5] However, due to the surge in AI's popularity, more data-driven AI diagnostics are being employed. For example, Yang utilizes flight trajectory data and motor speed data to detect faults as they arise onboard the UAV.[6] The methods and past research in the development of UAV damage detection focus on a solution that the technique provides, creating preventative measures that allow the controller to detect malfunctions of UAVs during pre-flight checks and early onboard time monitoring to prevent further costly damage to the UAVs.

Each solution provided is impressive in its paper, with its 85% detection of malfunctions.[5] They tend to only focus on how individually each method allows for accurate detection, with no comprehensive framework or interest in integrating multiple methods from acoustic, visual, vibration, and flight-data analytics to further capitalize on the strengths of different detection methods to allow quicker and more accurate fault detection. By gaining a deeper understanding of the interdisciplinary approach of each method together than in the problem of preventable malfunction, the risk of catastrophic failure will be mitigated, thereby improving UAV safety for both consumer and military uses. This paper argues that allowing multiple damage detection frameworks to work together, utilizing AI-based image and abnormality recognition, AI analysis of flight, motor speed, and acoustic signals, and real-time onboard sensor data, enables more accurate fault detection.

Discussion

2. Traditional Damage Detection:

Most existing research papers on UAV damage detection focus on technology that detects damage on wind turbines or architectural designs.[7] Focusing on using Acoustic and Vibration data in order to measure if the propeller of the wind turbine is faulty. This section will examine the primary meth-

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ods researchers in orderemploy to collect data for data model fault detection.

2.1. Vibration Sensors:

A prominent method being explored most extensively is the use of vibration sensors. Vibration sensors in engineering settings provide information about a structure's integrity without requiring a thorough examination of the structure to assess it. The function of this sensor is to identify damage by detecting changes in multiple properties of a structure, including density, connections between modules, and stiffness variations in the structure's geometric and material properties.[8] These functions of vibration sensors detect early stages or subtle damages that can lead to future problems in the structure.[5]

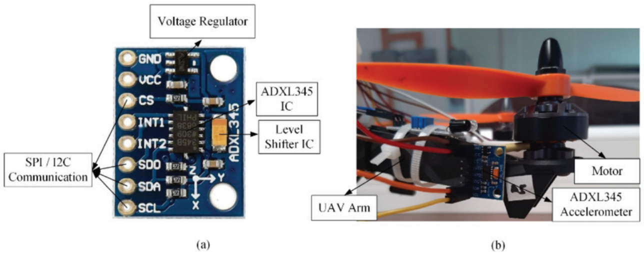

Figure 1: Annotated example of an accelerometer used to collect vibration data. Including the material used to create the ADXL345 accelerometer.[5]

In the context of UAVs, papers have been utilizing this technology to monitor dynamic changes in key components, including frames, motors, and rotors.[2] By analyzing the changes in vibration of these components, mechanics and operators of UAVs can detect shifts in frequencies within the UAV's body or an increase in motor frequency during operation, thereby inferring potential damage on board, as seen in (Figure 1).

Based on the paper written by Ghazali *et al.* on the effectiveness of vibration-based detection on a UAV, the vibration sensors were able to detect damage that commonly appeared. These common damages are propeller damage and wing damage.

Table 1: A data table of vibration data recorded using the ADXL335 accelerometer to prove the relationship between maximum amplitude and UAV damages.[5]

Configuration	Maximum Amplitude (g)	Average Absolute Amplitude (g)
Normal (Drone arm and propeller)	0.71	0.18
Minor crack (Drone arm)	0.89	0.22
Major crack (Drone arm)	1.82	0.46
10% Broken (Propeller)	0.83	0.22
25% Broken (Propeller)	1.65	0.55
50% Broken (Propeller)	3.46	1.5
Unbalanced (Propeller)	−1.72	0.41

To properly assess whether a vibration sensor can detect faults in a UAV, the best solution is to compare the data collected from a faulty UAV with a control dataset that represents a fully functional UAV without any faults. The data sets from the faulty drone arm dataset show a difference in amplitude when compared to the normal functional UAV dataset in Table 1. The minor crack in the drone arm has a maximum amplitude of 0.07, compared to a maximum amplitude of 0.03 from a normal drone arm configuration. The difference of 0.04 amplitude is a significant value in understanding the fault abnormalities that are occurring in the UAV. Since a difference can be found when comparing a minor fault to the arms of the UAV compared to a functional normal UAV, it's acceptable to believe this same conclusion would happen with a major fault. The same trend can also be seen when comparing vibration data from a faulty propeller UAV to that of a normal UAV propeller. The 10% broken propeller has a maximum amplitude of 0.05 compared to the 0.03 normal propeller maximum amplitude. This difference of 0.02, equivalent to the broken arm, is a significant value for detecting a fault with the UAV. Based on the data analysis, it's safe to assume that if the sensor can detect differences in the minor faulty UAV compared to the normal UAV, it can also detect faults within more catastrophic damage within a UAV.[5]

However, there are some drawbacks to using vibration sensors in assessing the faults of UAVs. Since the vibration sensors have not been implemented and adapted, the technology is not used within operational environments. Natural exterior variables that occur during the use of UAVs can affect the sensor's ability to detect faults during operations.[8] Another potential drawback of using vibration sensors is their offline nature.[8] The technology uses a recorded set of data from a pristine UAV to determine if the UAV is performing operations. Slight changes to the structure of the UAV will happen because of the prolonged use; the UAV may collect less or more amplitude data in the sensors. The increased amplitude from the data would create false detection when the UAV is safe to use.[8] Due to the nature of vibration sensors, which allow faults to be detected early before damage can occur, the technology falls short for either complex, non-standard damages or abrupt, catastrophic failures, such as sudden engine burnout or battery explosions. However, vibration sensors aren't the only technology being used to detect faults within UAVs; propellers and motors are also important components within a UAV. Sound-based detection is being explored to further enhance UAV fault detection.

2.2. Acoustic-Based Sensors:

Sound-based fault detection functions by collecting different types of auditory data from the moving parts of a UAV, from normal healthy motors, functional propeller, propeller failure, eccentric failure, and bearing failure, all of which are common faults seen in UAVs.[9]

Finally, the auditory data is then processed through various algorithms to properly differentiate between different malfunctions within the internal microphone of the UAV.[9]

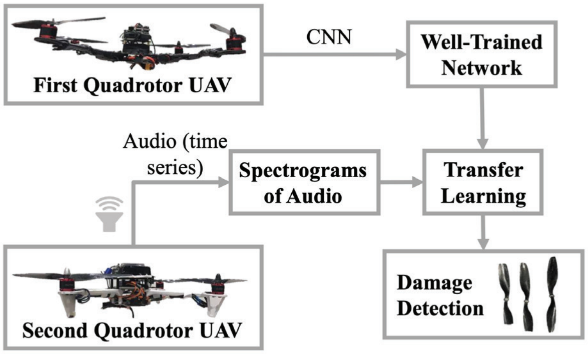

Figure 2: Flow chart showcasing the process for the collection of acoustic data of the UAV and how it's being used in Fault detection.[10]

Recent research demonstrates the potential future of technology for fault detection, while also sparking discussion on potential onboard usage and AI integration.[3-9,10] In the first paper, the author Ayhan explores the use of algorithms to assist in detecting common faults using sound data collected.[3] The microphone recorded four different sound data sets for the algorithm to learn from.[3] These sound data are processed through methods such as signal pre-processing and feature extraction, enabling algorithms to identify faults within different UAVs. This flow chart is observed in Figure 2.[10] The faults detected by the algorithms range from health Issues, propeller failure, motor failure, and bearing faults. The results concluded that regardless of the type of motor used, all algorithms trained on the datasets achieve 99% accuracy in detecting faults.

The paper notes that sound-based detection is fast and effective due to the use of algorithms that can pick up fluctuations in sounds that may signal faults.[3] Other papers, such as Steinhoff *et al.*'s paper, have replicated this experiment and found additional advantages to using sound-based detection, including the ability to isolate the fault's location within the UAV.[9] However, the drawback of using this method is the limitations of the data set. In the Ayhan paper, the motors of the UAV were placed within an empty room, ensuring that no major environmental sounds affected the collection of sound data during testing of the algorithms. Since the recorded data sets only recorded isolated UAV sounds, other environmental sounds may affect the algorithm's effectiveness in detecting faults within the UAV.

2.3. The Overall evaluation of traditional Damage detection and its effectiveness:

Overall, however, studies of vibration-based detection and sound-based fault detection strongly support the hypothesis that when AI is combined with more traditional, tangible methods, with advanced sensor data collection, it can provide accurate and effective breakthroughs for fault detection. As stated in the previous subsections, vibration sensors can detect minor changes in the physical body of UAV components by capturing shifts in amplitude, which can assist in identifying early stages of structural damage. However, it cannot adapt quickly.[11] The paper created by Ozkat mentions the offline nature of current vibration-based detection.[11] Based on the offline nature of the detection, slight changes resulting from wear and tear conditions of the UAV can cause false positives of faults in the UAV. The false positive occurs because the data is compared only with existing data from a perfectly manufactured UAV, which is unrealistic. With a sound-based system that accurately analyzes the auditory signatures of each UAV component.[12] Sound-based detection also has the added benefit of isolating fault locations within the UAV, which would enhance the utility of this direction.[13] The problem stems from its validated conclusion, which comes from controlled, low-noise environments, and is unrealistic for real-life usage.[13] However, these drawbacks can be alleviated by incorporating AI into traditional methods. AI can cross-reference data as well as make necessary judgments based on the environment to help assess better whenever a fault happens

3. AI Detection model:

With the rise of integrating AI into our technology, certain developments have been made to support AI usage in UAVs. The development of integrating AI has made reliable in-flight fault detection possible, while also improving existing fault detection methods.

The two primary studies that support this development are Yang *et al.*'s deep residual shrinkage network, used to enhance sound-based fault detection, but also uses flight path data to gather more accurate fault detection, and Pose *et al.*'s internal data-based detection, used to detect faults within propellers.[6–14]

3.1. Modal binning:

Within the paper proposed by Yang, a deep residual shrinkage network was developed and combined with wide convolutional layers to process motor speed and flight path data fully.[6] The network was created to minimize environmental sound data that may affect comparison, as well as to facilitate cross-referencing propeller status with existing healthy UAV data to identify faults.[6]

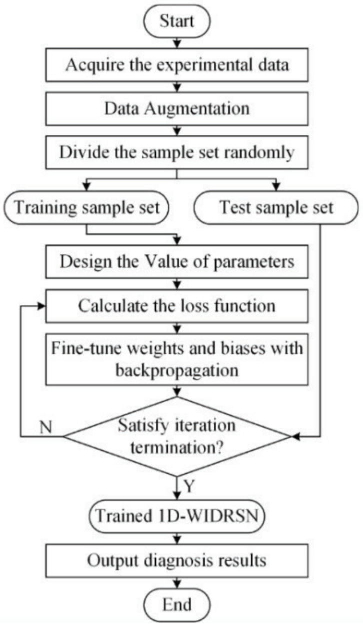

Figure 3: Flow chart describing the process of machine learning fault detection, as well as additional functions such as a loss function to reduce random error in data analysis. [6]

To create this network, the authors gathered flight logs containing flight path data, mainly roll value, pitch value, roll rate, pitch rate, yaw rate, and the angular velocities of the four propellers on the UAV or quadcopter, of a normal operating UAV, and various flight path data where a major fault happened. To determine if a fault is detected within the AI, when collecting real-time data from the drone, meaningful data from the sensors implanted within the UAV was extracted while filtering out possible noises from sound sensors and other detectors that may cause false positives within the AI.[6] The fluctuations and major differences detected with the meaningful data are compared to the dataset of fault examples to determine if faults are happening and isolate where the damages are located. This is a simplification of the entirety of the process of machine learning for detecting faults, in which the whole process is viewed in Figure 3.[6]

Based on how the technology functions, using AI for fault detection has the same benefits as using traditional sensors, including the ability to detect minor faults within a fraction of a second. The AI also has the added benefit of filtering out possible irrelevant data, such as environmental noises outside the UAV, to yield high detection accuracy, potentially helping to mitigate one of the drawbacks of using only sound and vibration fault detection. Finally, due to how the AI was trained to detect faults, it lacks the universal adaptability of traditional means. When migrating this technology to different UAVs, new datasets need to be trained, as no two UAVs are identical, which may decrease detection accuracy if the same AI is used across multiple UAVs.

3.2. Autoencoders:

Another paper created by author Pose also trained the composite model using similar methods, such as classifiers and neural networks, to measure any abnormal data within the UAVS; however, instead of focusing on using different data sets to determine a specific component with faults.

Pose develops a damage classification and estimation of fault using inertial measurement data and control inputs from the UAV.[14] The AI uses this data to accurately categorize the damage type of each component in the UAV and employs a regression-type model to estimate the severity of the fault by comparing real-time data with the extent to which it deviates from example flight dynamics.[14] Similar to Yang *et al.*'s paper on using AI in fault detection, Pose utilizes inertial data collected from various scenarios that a UAV may encounter during operation (healthy, motor-damaged, etc.). The subtle changes in data can indicate a potential fault.[14] Although the paper focuses on using inertial data for the AI to determine faults, the author also expresses the potential adaptability of the AI.[14] The purpose of the AI was to provide a robust, scalable, and platform-agnostic solution for fault detection that utilizes only the basic data collected from UAVs, including Inertial data and control inputs, for in-flight fault detection.[14]

Based on how the paper describes the solution's functionality in addressing fault detection, the use of Autoencoders has several functions that mitigate sensor limitations. Since the AI is trained on a universal dataset available for all UAVs, this allows the AI to be implemented across multiple UAVs without any changes needed.[14] However, inaccuracy was expected due to the limited data provided to the AI—the autoencoders, however, average 98.8%.[14] One thing to note about the paper is that, by focusing only on inertial data and flight control data, it lacks the precision of sensors to monitor both structural health and propeller health effectively. Finally, since AI has a structure that allows it to analyze other data sets independently, if this method is applied to more traditional fault detectors, such as sound or vibration, the success rate of fault detection will increase.

4. Integrating Artificial Intelligence and Existing Methods:

AI is an excellent tool for addressing fault detection in UAV development today; however, it sometimes lacks the necessary data and equipment to precisely detect faults in the integral parts of the UAV. This section aims to explore new and innovative papers that have delved deep into the exploration of combining AI and sensor-based detection.

Papers from NASA and Al Haddad featured how the UAV collects data within itself and how AI utilizes both the collected data and other unique data to detect faults. The IMU, or inertial measurement unit, is measured using the accelerometer. This data is then processed through various algorithms to effectively remove unnecessary data that could potentially lead to false detection within the UAV. The algorithms involve using low-pass filtering to remove high-frequency noise, aiming to strike a balance between temporal resolution and feature stability.[13] However, this isn't the only way the data gets processed, as there are currently two methods. PSD, or Power Spectral Density, measures the power used within a specific frequency range; this is used to determine if a component is not producing enough work despite the power being applied. The PSD method is especially great for detecting defect-related frequencies (bearing fault harmonics).[15] However, the discussion within the paper mentions that this method's inability to detect faults or health within components is mainly due to attenuation and mixed sources, which require more power.[15] Rather than manually analyzing the data processed by the PSD, both papers also employ AI or algorithms to analyze the data. Modal binning is a method used to detect faults. This method works by setting predefined data sets for different states of each UAV component, ranging from healthy to various types of malfunctions (bearing failure, signal failure, etc.).[15]

Comparing the data to either the pre-mandated data set or deviating from each data set could provide insight into whether a fault is occurring.[15] Another method used is Unsupervised Autoencoders, which are trained using flight data recorded from different normal, fault-free UAV operations with this methods also being used extensively outside of the 2 papers mentioned in which Chuanjiang Li *et al.*'s paper on integrating autencoder as a verification process of fault detection by using a generator consisting of two encoders and one decoder for the different classification of damage.[15,16]

These models learn to compress each UAV's healthy state data and then reconstruct the current UAV state using input features such as vibration signals, UAV attitude measurements, and motor RPM data.[15,16] During operation and fault analysis, the difference between these features and the reconstruction is referred to as the reconstruction error by the paper, which is utilized as a possible fault detection signal.[15] Higher error scores indicate that the current UAV data do not resemble normal, healthy patterns; therefore, a potential fault may occur.[15]

To reduce false alarms caused by environmental noise and variations in flight dynamics, pre-processing techniques such as those described in Section 3 are employed.[15]

Conclusion

In this paper, fault detection methods are discussed and explored to further interest in this technology. Data collection methods of vibration sensors, acoustic sensors, flight path, and motor speed data were explored, and data processing techniques such as signal preprocessing and feature extraction helped AI analysis methods work better. Although both methods of detecting faults are effective within their own functions, they have limitations that the opposite methods can mitigate. Data collection methods effectively identify minor faults within the UAV; however, they face challenges such as environmental noise, a lack of adaptability in operational conditions, and a limited scope in detecting complex or sudden faults. AI, although effective in analyzing complex and unique datasets—such as IMU data, flight trajectories, and acoustic signatures — to find faults, suffers from a lack of precision that normal data collection methods have in identifying minor faults. The paper summarizes how studies reviewed hybrid frameworks where AI refines and supports vibration and sound-based diagnostics by adapting and analyzing non-linear data sets and contextualizing sensor inputs within the UAV data. The way AI architectures are trained on universal datasets enables transferable fault detection solutions that can be deployed across various UAV designs without requiring additional training. Looking further, creating a hybrid framework that combines AI analysis with precise data collection from sensors enables effective fault detection, paving the way for fault localization and damage severity analysis. The application of AI in existing fault detection allows UAVs to self-assess and communicate their operational status autonomously during operations.

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■ Authors

Le Nam Son is a current senior attending International High School of Ho Chi Minh City in Ho Chi Minh, Vietnam. He is passionate about innovation within Engineering and aims to bridge the gap between Art and Engineering.