Applications of Machine Learning Techniques for Fault Diagnosis of UAVs

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Abstract

Due to the heavy usage of Unmanned Aerial Vehicles (UAVs) and the co-evolution of modern technologies, a crucial introduction to fault diagnosis has taken place in recent studies in the avoidance of ravaging consequences. Machine Learning techniques are one of the other major fault-diagnosing approaches in the field of Artificial Intelligence. This review article delivers an elaborated overview of the latest studies concerning UAVs fault diagnosis utilizing Machine Learning and Deep Learning techniques. A summarized comparison of the different methods is distinguishably elaborated where the conclusion highlights that research on fault diagnosis systems is progressing and yet to end. Consideration should be given to a growing number of research and methodologies.

Keywords

Unmanned Aerial Vehicles, Fault Diagnosis, Machine Learning, Artificial Intelligence, Artificial Neural Network

1. Introduction

Usage of Unmanned Aerial Vehicles (UAVs) has exhibited an expeditious escalation recently. UAVs are employed across many civil applications [1]. They provided a significant role in Infrastructural, Agricultural, Transporting, Security, telecommunications, and many other applications. In the past decade and in contrarily, UAVs have been used in aerial surveillance for military purposes. State, local and federal governments, including government officials among many thrived countries, employed UAVs for aerial surveillance [2]. UAVs were also implemented in monitoring Power transmission lines [3]. Now that UAVs are employed in both civil and military applications, studies regarding effectiveness and endurance have risen in the past years [4]. Their ascendancy gives them the privilege of replacing humans in jobs that can be repetitive, hard, or even dangerous [5]. While relying on UAVs for performance is increasing, faults started occurring despite the modern technologies and advanced manufacturing. A UAV system is partially composed of other subsystems, which are consistently vulnerable to faults. In order to avoid defects, a prediction of faults in a manner of fault diagnosing methods has taken place in many recent studies on different fields and applications.

Fault diagnosis means diagnosing the event of deficiencies within the utilitarian units of the process, which leads to undesired or intolerable behavior of the complete framework. Studies and reviews on fault diagnosis of variant applications have escalated rapidly in recent years [6, 7, 8, 9, 10, 11, 12], as many application areas have taken an interest in their beneficent conclusions. Helicopter UAVs fault diagnosis [13] is one, and sensor fault diagnosis [14] is two. Fault diagnosis can be achieved by signal processing or machine learning approaches, or based on both. Noting that, a recent study showed that implementing machine learning onto signal processing is sufficient [15]. Figure 1 describes the different methods of fault detection and isolation (FDI). Minimizing machine learning into hardware and analytical redundancy. This review paper will elaborate on machine learning methods in fault diagnosis. Machine learning is one of the major data-driven approaches in fault diagnosis and has been used in many variant aspects regarding UAVs. Figure 2 categorizes the machine learning methods into three approaches: supervised, unsupervised, and reinforcement learning. Artificial Intelligence (AI) is evolving in both the short and long-term processes [16, 17]. Machine learning (ML) methods have predicted the battery life of UAVs more efficiently than general methods of physics failure [18], especially in non-stationary vibrations [19]. Usage of UAVs in communication has also led to various problems, problems that were solved by adopting machine learning methods [20, 21]. Real-life scenarios of security monitoring wildfires using machine learning methods have demonstrated the effectiveness of fault detection in many aspects [22]. Another application is the detection of the disastrous citrus greening, where drones proved to be more efficient regarding inspections due to their wide coverage. Machine learning methods for citrus greening diagnosis were discussed, compared, and elaborated on, demonstrating their high accuracy in fault diagnosis [23, 24**?**].

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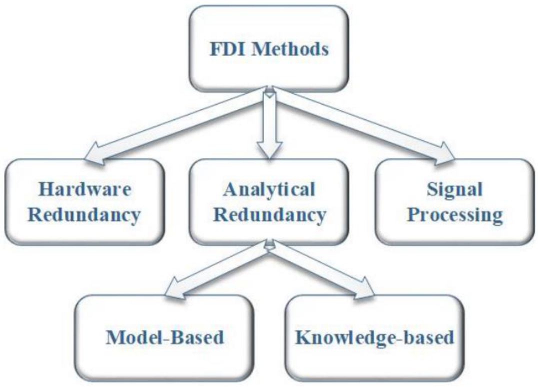

Figure 1: Fault Detection and Isolation (FDI) Methods Classification [5]

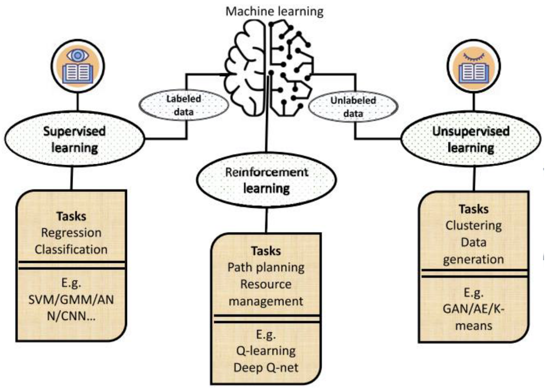

Figure 2: Machine Learning Overview[28]

2. Commonly Applied Machine Learning Methods For UAVs Fault Diagnosis

The progression in machine learning techniques, sensors, and IT innovations have opened the entryways for UAV applications in numerous divisions. The main divisions, be that as it may, are wireless networks, military, agribusiness, mining, and many others [25]. In a short time, implementing machine learning techniques to detect faults in UAVs has taken the attention of numerous previous research studies that that involve. Where it is essential to consider the authenticity and originality of the acquired dataset utilizing signal processing or other approaches [26, 27]. While different methods were used, this review paper has considered the most common modern techniques and approaches. Overview of exiting research studies on fault diagnosis of UAVs using machine learning techniques are listed in Table 1.

2.1. Artificial Neural Network ANN

Artificial Neural Networks (ANNs) are known to be the most commonly used method of machine learning approaches as they have evolved due to their flexibility and ease of coding[48, 49]. In [29], a prototype of a fault diagnosis pattern to identify and recognize damaged blades of a multirotor UAV was used. The ANN was introduced to identify some particular features of emitted acoustic emissions and signals. In the proposed technique, an accurate fault classifier prospered. The recordings of the noise emissions from a UAV were utilized to construct a classification model to identify the unbalances of blades in a UAV blade [36]. The authors have developed a model based on an artificial neural network to detect the unbalances of a quadcopter blade. The indoor test experiments have shown a promising fault detection method in UAV blades. Hence, below are the most popularly used NN techniques in this regard.

2.1.1. Convolutional Neural Network CNN

CNN is of wide-range use [50]. In [30], the authors have introduced a price-conscious fault detection method in a large fixed-wing UAV. Six different classifiers were used where the convolutional neural network-based classifier reflected good accurate results despite the longest time of these results. The experimental results have demonstrated an effective model to reduce expenses on computing equipment that ensures the same overall efficiency of the fault diagnosis system. The work in [31] suggests a method to localize the acoustic emissions in plate-like structures. One sensor and a convolutional neural network algorithm were used where intentional small damages were made to the system. This work can be similar to a fixed-wing UAV structure. Audio noise was recorded during the flight of a UAV with a damaged propeller, where the detection model was trained based on the convolutional neural network in [35]. Augmentation of transfer learning with deep learning has made the CNN more functional based on experimental data validation. The authors of [43] have taken actual test flight data of a fixed-wing UAV and implemented them in a compound fault diagnosis and labeling method. Five classifiers were used, including a fully convolutional neural network (FCNN) and a modified CNN. The diagnosing performance is improved according to the experimental results and comparison of the five methods.

2.1.2. Long and Short-Term Memory Neural Network LSTM NN

In [38], an airborne acceleration sensor is used to detect faults of blades in a quadcopter using a long and short-term memory neural network-based model. The accuracy of this algorithm is proved to be sufficient compared to

Table 1
Summary on existing studies on fault diagnosis of UAVs using machine learning

Machine Learning Method	UAV Type	Part of Fault Detection
Artificial Neural Network [29]	Quadcopter	Damaged Blades
Decision Tree and Convolutional Neural Network[30]	Fixed-Wing	Maintenance purposes
Convolutional Neural Network [31]	-	Health monitoring
Support Vector Machine and K Nearest Neighbor [32]	Fixed-Wing	Damaged Wing
Self-Organizing Map [33]	Quadcopter	Motor base loosening and Damaged blades
K Nearest Neighbor [34]	Quadcopter	Damaged Blades Loosening of Motor Screw and Loosening of Arm Screw
Convolutional Neural Network [35]	Quadcopter	Damaged Blades
Artificial Neural Network [36]	Quadcopter	Unbalanced Blades
K Nearest Neighbor[37]	Fixed-Wing	Amplitude in normal achieved flights
Long and Short-Term Memory Neural Network [38]	Quadcopter	Damaged Blades
Deep Residual Shrinkage Neural Network [39]	Quadcopter	Damaged Blades
Radial Basis Function Neural Network [40]	Quadcopter	Actuators
Long and Short-Term Memory Neural Network [41]	Fixed-Wing	Wing
Support Vector Machine[42]	Quadcopter	Gyro and Accelerometer
Convolutional Neural Network [43]	Fixed-Wing	Wing
Decision Tree, Support Vector Machines and K Nearest Neighbor [44]	Quadcopter	Motor, Bearing and Blades
Back Propagation Neural Network[45]	Quadcopter	Sensors
Radial Basis Function Neural Network [46]	Fixed-Wing	Sensors
Fuzzy Neural Network [47]	Fixed-Wing	Actuators

other neural networks, while the vibrations signals in the airframe were recorded experimentally and translated into codes using the fault diagnosis method. A fixed-wing UAV fault diagnosis system based on five models, one of which was a long and short-term memory neural network [41]. Convenient predictions were provided based on numerical simulations.

2.1.3. Radial Basis Function Neural Network RBF NN

In [40], the authors have introduced a fault-tolerant control approach to detect actuator faults in a quadcopter. A normal adaptive sliding mode control is combined with a radial basis function neural network, introducing a modified adaptive sliding mode control approach. An experimental, numerical comparison between the two is elaborated, showing the significant role of a radial basis function network. The authors of [46] have implemented machine learning neural networks into the fault detection methods. A radial basis function neural network was used to minimize time due to the algorithm's flexibility when dealing with nonlinear environments. Sensor faults in fixed-wing UAVs are proved to be easily detected using the proposed system experimentally and statistically.

2.1.4. Other Neural Networks

In [39], the authors have developed and upgraded the used neural networks. Damaged blades in a quadcopter diagnosis based on a deep residual shrinkage network and an extra convolution layer have both emerged to produce an upgraded neural network algorithm named 1D-WIDRSN. The experimental statistical analysis has shown the effectiveness and accuracy of the hybrid algorithm compared to normal neural networks. have used a back propagation neural network (BPNN) as a machine learning method to diagnose faults in a sensor of a quadcopter. Then, it was optimized by a genetic algorithm to fasten the convergence. The results are shown experimentally, supporting that enhanced BPNN is more efficient in fault diagnosis. A strategy of scattered fault-tolerant cooperative control to acquire a synchronized track control of UAVs was introduced in [47] by using fuzzy neural networks. An experimental approach where the following UAV tracks the behavior of the leading UAV is conducted regardless of the actuator faults. The simulation results are then discussed to prove the adequacy of the proposed strategy.

Table 2
Fault Diagnosis ML Methods comparative results

Machine Learning Method	UAV Type	Part of Fault Detection
ML Method	Fault Detection Part	UAV type
CNN 17.4%	Blades 32%	Quadcopter 57.89%
K-NN 17.4%	Wing 16%	Fixed-Wing 36.84%
SVM 13%	Motor 12%	
ANN 8.7%	Actuators 8%	
LSTM NN 8.7%	Motor Bearing 8%	
RBF NN 8.7%	Sensors 8%	
DT 8.7%	Others 16%	
SOM 4.3%		
Other NN 13%		

2.2. K Nearest Neighbor K-NN

The work in [32] describes preliminary damage diagnosing and classification system for a fixed-wing UAV. The system includes a description of data analysis from a piezoelectric sensor system with independent component analysis and machine learning methods. One of which was the subspace K-nearest neighbor with the best results and accuracy. In [34], variant faults in a quadcopter UAV were examined in a fault diagnosis system. Damaged parts were blades, armature eccentric, and motor base loosening. Pulse and vibration signals were recorded and analyzed using a machine learning method employing K-NN. Experimental results demonstrate the high efficiency of the used method. Authors of [37] suggest an innovative system for fault diagnosis of fixed-wing UAVs (FW-UAVs), where the procedure dynamics, operation conditions, changing data density, and procedure disturbance are evaluated. A modified algorithm utilizing Shared Nearest Neighbor based Distance (SNND) and a K-Nearest Neighbor algorithm hiring SNND (SNND-KNN) was proposed to realize offline operation condition classification and online identification. The results have confirmed the suitability of algorithms for fault diagnosis of FW-UAVs. Generally, the malfunctions of blades, bearings, and eccentrics are well-known in motors of UAVs. The recorded sound data of the motors were analyzed in a fault diagnosis system of the mentioned malfunctions in [44]. Important feature extraction employing signal processing and different machine learning techniques, including K-NN, were used in the system network where all algorithms proved high result efficiency. High accuracy in the proposed approach demonstrated that the study would put up to the reflections in the pertinent field.

2.3. Self-Organizing Map SOM

The authors of [33] have embraced the self-organizing map machine learning method, which is an unsupervised assembling method to exhibit a model for diagnosing health status in a quadcopter UAV. Vibration features of three flight conditions (normal, motor base mount loose, unbalanced broken blades) were recorded and trained in a system that has assembled variant vibration patterns of fault situations. The experimental results have proved that the method can also predict the occurrence of the fault, not only diagnose it.

2.4. Support Vector Machine SVM

SVM is used in many different aspects [51]. In [42], the authors simulated an aircraft model and utilized it to generate data and test some designed algorithms. The simulated measurements were collected from random flight data. A supervised fault diagnosing method based on SVM was utilized to identify the faulty and nominal flight states in loss of effectiveness in control surfaces of a drone UAV. Results encourage the use of SVM in fault diagnosis due to accurate and effective acquired accuracy. Furthermore, as discussed in subsection 2.2. the authors of [32] have also adopted the use of support vector machine in fault diagnosis. An average result accuracy was obtained using SVM. In addition, authors of [44] and aand as discussed in subsection 2.2, have adopted the SVM where the best results were acquired based on it

2.5. Decision Tree

As discussed in subsections 2.1.2 and 2.2, the authors in [30] and [44] have adopted the decision tree method in machine learning fault diagnosis where Gradient-based decision tree have showed better accuracy over normal decision tree machine learning methods.

3. Conclusion

According to the statistical analysis of table 2 and based on this review article, we have concluded the following:

- Neural Network Methods are the most used techniques concerning fault diagnosis of different part of UAVs with a total percentage of 56.5
- Blades are more vulnerable to damage conditions as their percentage is over 30% in the parts were recent studies conducted fault diagnosis on.
- Type of UAV percentages proves that drones are on a heavy usage term and hence more susceptible to damage .

Adding up, the developing request for secure flights of unmanned aerial vehicles requires modern and worldly-wise fault diagnosis methods not only for faults in blades and wings but also in other UAV subsystems. In this respect, a promising approach that appears to have captured the attention of researchers in recent years is the hybrid fault diagnosis methods that delicately address the undesired behavior of an unmanned aerial vehicle based on combined machine learning techniques or/with signal processing for important feature extraction.

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