DAMAGE IDENTIFICATION FOR MULTI-ROTOR DRONE USING CONVOLUTIONAL NEURAL NETWORK TECHNIQUE

By

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In contemporary society, multi-rotor drone have found extensive usage in various fields, such as agriculture, cargo transportation, and aerial photography. Damage to multi-rotor drone can compromise their safety and reduce efficiency. Therefore, early damage detection is crucial as it can prevent catastrophic failures and decrease the associated economic and human costs. At present, visual inspection is the primary method used for detecting damage in multi-rotor drone. However, this technique may not be entirely reliable in identifying minor faults that are difficult to discern with the naked eye. This study focuses on three experimental parts; firstly,to fabricate a multi-rotor drone as the research subject; secondly, to develop a vibration data acquisition device with MPU6050 and STM32 micro-controller,and thirdly,to identify the damage using machine learning techniques. Damage scenarios were set by releasing the bolts at different conjunction points of the multi-rotor body frame.Three damaged cases were set by releasing one bolt at arm conjunction, two bolts at arm conjunction and one bolt at motor conjunction, respectively. The first case (undamaged) is considered as the reference. Any change in structure can reflect in a vibration signal. Three axes vibration data were acquired under different conditions,for the sake of safety,the UAV was conducted under the ground with a idol motor speed. After the data collection,the data preprocessing techniques linear interpolation method Laida criterion were adopted to process the missing data and inconsistent data.For damage identification,three machine learning techniques, including decision tree, random forest, K-Nearest-Neighbours (KNN) were adopted to identify the damage for multi-rotor drone and finally with the accuracy of 68.74%, 67.96%, 91.71%, respectively. Then, Convolutional Neural Networks (CNN), as the state-of-the-art machine learning technique also called deep learning was proposed and achieved outstanding success with 100% accuracy for damage identification. It is important to consider the parameter used in the CNN,so,in this research,the parameter used in the CNN,including sample length, convolution kernel, number of convolutional layer,activation function,batch-size,dropout,learning rate were analyzed by Python platform and the best parameter were selected.In summary, machine learning techniques can effectively detect damage for multi-rotor drone, however,CNN technique convolutional neural network possesses superior feature extraction capability and classification accuracy compared to traditional machine learning techniques.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENGENALAN KEROSAKAN UNTUK DORN MULTI-ROTOR MENGGUNAKAN TEKNIK RANGKAIAN NEURAL KONVOLUSI

Oleh

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Dalam masyarakat kontemporari, dron multi-rotor telah digunakan secara meluas dalam pelbagai bidang, seperti pertanian, pengangkutan kargo, dan fotografi udara. Kerosakan kepada dron multi-rotor boleh menggugat keselamatan mereka dan mengurangkan kecekapan. Oleh itu, pengesanan kerosakan awal adalah penting kerana ia boleh mencegah kegagalan yang merbahaya dan mengurangkan kos ekonomi dan manusia yang berkaitan. Pada masa kini, pemeriksaan visual adalah kaedah utama yang digunakan untuk mengesan kerosakan pada dron multi-rotor. Walau bagaimanapun, teknik ini mungkin tidak sepenuhnya boleh dipercayai dalam mengenal pasti kesilapan kecil yang sukar dilihat dengan mata kasar. Kajian ini memberi tumpuan kepada tiga bahagian eksperimen; pertama, untuk membina dron multi-rotor sebagai subjek kajian; kedua, untuk membangunkan peranti pengumpulan data getaran dengan MPU6050 dan mikro-pengawal STM32, dan ketiga, untuk mengenal pasti kerosakan menggunakan teknik pembelajaran mesin. Skenario kerosakan ditetapkan dengan melepaskan baut pada titik-titik sambungan berbeza rangka badan dron multi-rotor. Tiga kes kerosakan ditetapkan dengan melepaskan satu baut pada sambungan lengan, dua baut pada sambungan lengan, dan satu baut pada sambungan motor, masing-masing. Kes pertama (tidak rosak) dianggap sebagai rujukan. Sebarang perubahan dalam struktur boleh mencerminkan isyarat getaran. Data getaran tiga paksi diperoleh dalam keadaan yang berbeza, untuk keselamatan, UAV dijalankan di bawah tanah dengan kelajuan motor yang tenang. Selepas pengumpulan data, teknik pra-pemprosesan data seperti kaedah interpolasi linear dan kriteria Laida digunakan untuk memproses data yang hilang dan data yang tidak selari. Untuk mengenal pasti kerosakan, tiga teknik pembelajaran mesin, termasuk pokok keputusan, hutan rawak, dan K-Nearest-Neighbours (KNN) digunakan untuk mengenal pasti kerosakan dron multi-rotor dengan ketepatan masing-masing 68.74%, 67.96%, 91.71%. Kemudian,

Rangkaian Neural Konvolusi (CNN), sebagai teknik pembelajaran mesin terkini juga dikenali sebagai pembelajaran mendalam, dicadangkan dan mencapai kejayaan cemerlang dengan ketepatan 100% untuk pengenalan kerosakan. Penting untuk mempertimbangkan parameter yang digunakan dalam CNN, oleh itu, dalam kajian ini, parameter yang digunakan dalam CNN, termasuk panjang sampel, kernel konvolusi, bilangan lapisan konvolusi, fungsi pengaktifan, saiz batch, pengecualian, kadar pembelajaran, dianalisis dengan platform Python dan parameter terbaik dipilih. Secara keseluruhannya, teknik pembelajaran mesin dapat mengesan kerosakan dengan berkesan untuk dron multi-rotor, namun, teknik CNN, rangkaian neural konvolusi, memiliki keupayaan pengambilan ciri dan ketepatan klasifikasi yang lebih unggul berbanding teknik pembelajaran mesin tradisional.

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LIST OF ABBREVIATIONS

DDI	Damage Detection and Identification
SHM	Structural Health Monitoring
MEMS	Micro electro mechanical system
1-D	One dimensional
CNN	Convolutional neural network
SVM	Support vector machine
KNN	K nearest neighbour
UAV	Unmanned Aerial Vehicle Unmanned Aerial Vehicle
FAA	Federal Aviation Administration
IoT	Internet of things
VTOL	Vertical take-off-landing
NDT	Non-destructive testing
EKF	Extend Kalman filter
SFUKF	Suboptimal fading unscented Kalman filter
LSTM	Long and Short-term Memory
ANN	Artificial Neural Network
IMU	Inertial Measurement Unit
DWT	Discrete Wavelet Transform
FT	Fourier Transform
GPS	Global position system
ESC	Electronic Speed Control
GS	ground station
CCW	Counter-Clockwise
CW	Clockwise
SD	Secure Digital

SPI	Serial Peripheral Interface
SDIO	Secure Digital Input and Output
MCU	Microcontroller Unit

CHAPTER 1

INTRODUCTION

1.1 Background

In recent decades, the use of multi-rotor drone has become increasingly prevalent in both civilian and military contexts. Researchers have designed and fabricated various types of multi-rotor drone, ranging from single to twelve motors (Hassanalian et al.,2017). Among the most well-known types of multi-rotor drone are quad-copters and hexa-copters (Cai et al.,2014). multi-rotor drone are similar to helicopters, but instead of changing the angle of attack of the propellers, they control motion by varying the speed of different propellers. multi-rotor drone have rotating parts (propellers) and operate under complex and diverse conditions, making them susceptible to failure and structural damage. According to statistics, the accident rate of unmanned aircraft is 100 times higher than manned aircraft (Ozkat et al.,2023).

Structural health monitoring (SHM) has become an essential area of research in modern industry, with damage detection and identification (DDI) being a critical component (Glisic et al.,2009). Early methods for detecting damage relied on visual inspection techniques, which were found to be both time-consuming and inaccurate (Worden et al.,2000). In the aerospace industry, vibration-based damage detection has been studied since the late 1970s and early 1980s in conjunction with the development of the space shuttle (Farrar et al.,2001). However, research on damage detection and identification of multi-rotor drone is limited.

This study aims to address this gap by focusing on the detection and identification of damage in multi-rotor drone using state-of-the-art deep learning technology. A quad-rotor aircraft was fabricated as the experimental object, and a vibration data acquisition device was designed to collect the vibration data using the MEMS sensor MPU6050. The thesis describes the fabrication process of the quad-copter and the data acquisition device. A 1-D convolutional neural network (1-D CNN) was proposed to detect four structural conditions based on the vibration signals. Other damage detection algorithms were also discussed and compared, including KNN, decision tree, and random forest.

1.2 Problem statement

Damage is unavoidable with the increase in working hours and the complexity of the multi-rotor drone. The aftermath of such damage invariably manifests in the form of system malfunction and subsequently drives up maintenance costs or, at worst, leads to catastrophic failure of the unmanned aerial vehicle (UAV)

(Puchalski et al.,2022). Hence, early detection and damage identification are indispensable for optimal UAV performance (Bowkett et al.,2018).

Structural damage, such as propeller damage and loosened parts, constitutes the most prevalent form of damage experienced by multi-rotor UAVs (Al-Haddad et al.,2023). However, such damage often goes unnoticed until it reaches catastrophic proportions or culminates in UAV crashes.

In recent years, a plethora of studies have been conducted on damage detection and identification, which primarily involve two distinct approaches: model-based and data-driven methods (Vural et al.,2016). The most significant challenge associated with the model-based method is the need for a highly accurate mathematical model, which is often difficult to achieve (Făgărăşan et al.,2008). On the other hand, the data-driven method has gained widespread use in damage detection research in recent decades. However, this approach presents several challenges that warrant consideration. Specifically, these problems can be delineated as follows:

1. For most UAV, there is no data interface, so, it is hard to acquire the data, it usually need extra device or to change the structure of the UAV to collect the data.
2. The data collected by extra device usually not very complete which will affect the feature extraction by machine learning techniques for damage identification.
3. Deep learning model has strong ability in feature extraction from raw data, however, there is no unified standard for the model, especially the parameter in the model.

All the problems are being researched in this thesis. Deep learning as the latest artificial intelligence technology has shown a strong ability in damage detection and identification. This thesis discussed the “standard” of deep learning convolutional neural networks and compared it with traditional technology.

1.3 Research objectives

The purpose of this research is to develop an innovative damage detection technology based on a deep learning algorithm to facilitate early detection and identification of damage in multi-rotor UAVs, thereby preventing catastrophic failure. The specific objectives of this study are as follows:

1. To investigate how to design, fabricate and assemble quad-rotor drone and vibration data acquisition device.
2. To collect vibration data under bolts loosen conditions and analysis the vibration data with pre-processsing methodology .

3. To explore machine learning methods and deep learning methods for damage identification and find the best parameter setting.

1.4 Research scopes

The scope of this research involves the fabrication of a quad-rotor UAV as the primary object for damage detection and identification. To fabricate the UAV, the components of UAV need to be reviewed. Based on the mission of the UAV, the suitable components need to be researched and selected. Vibration data will be utilized for feature extraction, and to overcome the challenge of data acquisition, a data acquisition device will be designed using STM32 single-chip microcomputer and MPU6050 sensor. A C language program will be developed to facilitate data collection. Inevitably, the collected data will contain missing and abnormal data. Hence data processing technology will be adopted to mitigate these issues.

Traditional machine learning methods will be utilized to detect damage, and the results will be compared with the proposed 1-D CNN model for damage detection and identification. All damage detection algorithms will be implemented on the Python platform. The research scope will be limited to the evaluation of the effectiveness of the proposed CNN model and its potential to enhance damage detection and identification in multi-rotor UAVs.

1.5 Research limitations

The limitations of the research are:

1. Limited fault types were researched and damage scenarios were generated by loosening bolts, however,the severity of the damage can not be quantified.
2. The vibration data were collected under an idling on the ground, in other words, the damage identification process is not in real-time.
3. This thesis discussed the parameter of the CNN; however, the configuration for these parameters remains opaque. In the future, there is potential for studying optimization algorithms to identify the optimal structure and parameters for the network.

1.6 Thesis Layout

This thesis is divided into six chapters which can be listed as follows:

Chapter 1: This chapter introduces the background of damage detection and identification in UAV, and emphasizes the reason and the significance of damage detection for UAV. The problem statement, research objectives, scopes and thesis layout are also explained briefly.

Chapter 2: This chapter comprises a review related to the research including: the introduction of UAV, SHM technique, and the methods for damage detection of UAV in the previous research. Two types of methods including model-based and data-driven method are reviewed, and the data-driven methods are mainly illustrated because this thesis also adopted the method. Base on different types of data, four methods including vibration, sound, temperature and onboard sensor data were mentioned in this chapter.

Chapter 3: Chapter 3 illustrates the flow chart of the research. In this chapter all details of experimental work are described such as: the multi-rotor UAV fabrication design, the vibration data acquisition device design, data collection setting, and data processing technology. All the processes of this work are detailed in this chapter.

Chapter 4: This chapter checks the results of damage detection and identification based on vibration signals by applying both machine learning and deep learning methods. Data preprocessing technology and the detail of the 1-D CNN were introduced in this chapter.

Chapter 5: The results of the experiments were discussed in this chapter and the results of machine learning methods and CNN was compared. Furthermore, the influence factor of CNN was discussed and verified in this chapter.

Chapter 6: The main findings of this research are presented in this chapter, while the contribution to the scientific knowledge of this work is also presented. Moreover, the limitations of this research and recommendations for future work are provided in this chapter.

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