An Audio-Based Fault Diagnosis Method for Quadrotors Using Convolutional Neural Network and Transfer Learning

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Abstract—Quadrotor unmanned aerial vehicles (UAVs) have been developed and applied into several types of workplaces, such as warehouses, which usually involve human workers. The co-existence of human and UAVs brings new challenges to UAVs; potential failure of UAVs may cause risk and danger to surrounding human. Effective and efficient detection of such failure may provide early warning to the surrounding human workers and reduce such risk to human beings as much as possible. One of the commonest reasons that cause the failure of the UAV’s flight is the physical damage to the propellers. This paper presents a method to detect the propellers damage only based on the audio noise caused by the UAV's flight. The diagnostic model is developed based on convolutional neural network (CNN) and transfer learning techniques. The audio data is collected from the UAVs in real time, transformed into the time-frequency spectrogram, and used to train the CNN-based diagnostic model. The developed model is able to detect the abnormal features of the spectrogram and thus the physical damage of the propellers. To reduce the data dependence on the UAV’s dynamic models and enable the utilization of the training data from UAVs with different dynamic models, the CNN-based diagnostic model is further augmented by transfer learning. As such, the refinement of the well-trained diagnostic model ground on other UAVs only requires a small amount of UAVs training data. Experimental tests are conducted to validate the diagnostic model with an accuracy of higher than 90%.

I. INTRODUCTION

In recent years, considerable attention has been paid on unmanned aerial vehicles (UAVs) due to its broad application in many areas such as transportation [1] and infrastructure monitoring [2], [3]. Given the high risk of the pilot fatality, the early idea about UAV usage is reconnaissance missions in military around 1960 [4]. Semsch et al. [5] presented an occlusion-aware mechanism to allow multiple UAVs to complete persistent surveillance in complex urban environments. Han et al. [6] utilized a bunch of low-cost UAVs to detect the nuclear radiation of a certain region periodically and efficiently. Abdelkader et al. [7] combined a swarm of UAVs with Lagrangian microsensors and generated a real-time flood map with short-term flood propagation forecast to reduce casualties.

No matter in which field, the dynamic stability of UAVs is the premise of sophisticated scenarios. Therefore, the topic of the diagnosis on UAVs has attracted extensive research interest. Hansen et al. [8] applied parameter adaptive estimators to develop a diagnostic scheme to detect airspeed sensor fault. Avram et al. [9] developed a diagnostic scheme by estimating the roll and pitch angles ground on the inertial measurement units (IMUs) of UAVs. Younes et al. [10] introduced an output-estimator to detect the sensor fault. The signals from the fault sensor could affect some computational commands of the actuators.

Meanwhile, compared to the UAV sensor failure, the physical damage to the propeller could bring more serious consequences. UAVs might lose the flying balance when the damaged propeller rotation cannot maintain the desired lift force, and fall directly. The crucial concern that is human beings’ life safety is threatened by this physical failure. Benini et al. [11] developed a damaged propeller blade detection model based on the acceleration signals from the IMU of a UAV. Ghalamchi et al. [12] identified the broken propeller by detecting the physical damage vibration data provided by a built-in accelerometer. Rangel-Magdaleno et al. [13] implemented Discrete Wavelet Transform (DWT) decomposition and Fourier Transform to process audio data collected from a real experimental test, and used some statistical parameters based on audio data to discriminate the broken propeller.

The audio data indicates the noise amplitude of UAVs, and there are several approaches to analyze the abnormal behavior of UAVs based on it. The commonest one is spectrogram. Harmanny et al. [14] utilized spectrogram to distinguish birds and mini-UAVs based on the radar micro-Doppler. While even it is possible to detect the broken propellers from the spectrogram of the vibrations by human, the efforts on some tremendous amount of works still could be a huge burden of human beings. In terms of accuracy and efficiency, deep learning techniques have started to show great potential in the fault detection areas [15]–[21]. The CNN has shown great success in making decisions on image-based studies [22]–[25]. Researchers define the CNN code to split one image into several parts and extract some particular features. Hence, CNN can identify the distinction remarkably on image-based fault diagnosis. Wen et al. [26] proposed an approach to transfer the features of the raw data from datasets to two-dimensional images, and utilized a classical release of CNN named LeNet-5 to do fault diagnosis. Guo et al. [27] converted the residual signals from global positioning system (GPS), IMU and air data system (ADS) to time-frequency maps, and implemented the CNN to diagnose damaged UAVs ground on the extracted features of 2D maps.

Considering the trained neural network usually only shows decent performance on one specific model, it is desirable to exploit the generalization of fault diagnosis according to
a neural network. In the past decade, transfer learning has been spotlighted as a novel learning technique for extending the adaption of a model. Wen et al. [28] presented a supervised transfer learning based on sparse auto-encoder, and diagnosed fault by minimizing the discrepancy penalty between two tasks. Zhang et al. [29] utilized transfer learning to improve bearing fault diagnosis performance in different working environments. Cao et al. [30] realized gear transmission diagnosis with a small set of training data by transferring the knowledge from a well-trained neural network.

This study aims to provide a new yet easy deep learning method for the UAVs’ propeller fault diagnosis based on the 2D audio spectrogram. The audio data is collected from several actual UAVs. The traditional audio-based fault diagnosis which directly uses audio signal data to do analysis [31]–[33], while this paper converts the collected audio data to a spectrogram, the time and frequency are represented along with the horizontal axis and vertical axis, respectively. Therefore, a spectrogram, the time and frequency are represented along with the horizontal axis and vertical axis, respectively. Therefore, the audio signal is shown in the spectrogram continuously, which directly uses audio signal data to do analysis [31]–[33], while this paper converts the collected audio data to a spectrogram. CNN classifies the broken and unbroken propellers ground on using spectrograms as the input data. Additionally, transfer learning is employed to build up a generalized model for different UAVs with various testing scenarios. The results show this approach has an outstanding capability for the UAVs’ propeller fault diagnosis.

The remainder of this paper is organized as follows. Section II introduces the whole framework; Section III presents the data collection and pre-process; Section IV presents the diagnosis method based on CNN; Section V extends this method to different UAVs based on transfer learning; Section VI concludes this paper.

II. PROPOSED DIAGNOSIS SCHEME

Physical damage to the propellers of the quadrotor may cause unsteady flight or even flight failure. While several diagnosis techniques have been developed based on the control signals or the accelerations of the quadrotors as well as the dynamics, in this paper we present a model-free diagnosis method that is only based on the noise introduced by flight. It is easy to be implemented and does not require any additional sensors.

The overall scheme of the proposed diagnosis method, as illustrated in Fig. 1 includes the following key components: audio recorder to obtain the time-domain audio signals, spectrogram converter to transform the signals from the time domain to the time-frequency domain, CNN-based diagnostics, and transfer learning-based diagnostics. The audio data from Quadrotor A is received by the audio recorder in terms of time series, and then transferred to the “spectrogram” in the time-frequency domain which can be presented by two-dimensional images. These images are labeled by the scenarios indicating whether damaged propellers are included or not and used to train or test the diagnostics model using CNN. To make the trained CNN model to be extensible to other quadrotors, transfer learning is used to refine the CNN model when the audio source becomes a different quadrotor, denoted as Quadrotor B.

III. AUDIO DATA COLLECTION AND ANALYSIS

A. Audio data processing

The audio data indicates the amplitude of the noise along the time interval from UAVs. While there are still some audio characteristics that show in the frequency domain. Thus, this study uses a comprehensive presentation, “spectrogram”, which represents the audio signal features in both time and frequency domains. The audio data is transferred to a series of windowed segments, and the windowed segments are offset adjacent in the time domain with a certain percent. In a spectrogram, the time and frequency are represented along the horizontal axis and vertical axis, respectively. Therefore, the audio signal is shown in the spectrogram continuously, and the energy of the audio signal can be denoted as different colors at a particular time with a certain frequency. At each time instance $t$ and frequency $k$, the spectrogram $X(t,k)$ in the discrete-time domain is denoted as:

$$x(t,k) = \sum_{n=0}^{N-1} W(n) \cdot x(n+t \cdot h) e^{-2\pi i \frac{k}{N} n}$$  \hspace{1cm} (1)$$

where $w(n)$ is a Hann window with $N$ samples, $x(t)$ is the audio signal, and $h$ is the time shift between the continuous windowed segments.
Tests | Propeller Sets | Thrust Commands
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Configuration 1 | Four propellers in good condition | Low/medium/high
Configuration 2 | Three propellers in good condition plus propeller A | Low/medium/high
Configuration 3 | Three propellers in good condition plus propeller B | Low/medium/high

TABLE I: Test configurations

B. Experimental test platform and data collection

The platform mainly consists of quadrotors, an audio recorder, a computer, and several types of propellers with different levels of damages. In this paper, two assembled quadrotors with different frames, as shown in Fig. 2, are used for the data collection and experimental test. Well-balanced propellers and damaged propellers are shown in Fig. 3. The propeller labeled with C in Fig. 3 is in good condition and has a dimension of 10 inches for diameter and 4.5 inches for pitch. The length of the propeller labeled with A is 8.6 inches and the length of the propeller labeled with B is 9.6 inches, which illustrates the deflections for propellers A and B.

Three sets of tests are conducted for each quadrotor. Each set of test is with different propeller configuration. In order to obtain the quadrotors’ noise data in different speed scenarios, different thrust commands are applied for each set of tests as shown in Table. I. Three sets of thrust commands which are defined as low, medium, and high thrust commands, are given through the radio control with a frequency of 2.4 GHz. A microphone records the audio with a duration of 6 seconds as a sample of data. Data samples are presented as the form in Fig. 4 and Fig. 5.

![Fig. 2: Quadrotors used for experimental test](image1)

![Fig. 3: Propellers used for experimental test](image2)

![Fig. 4: Audio signals generated from the test with broken propeller](image3)

![Fig. 5: Audio signals generated from the test with unbroken propeller](image4)

![Fig. 6: Spectrogram generated from the test with broken propeller](image5)
The dimension of the feature maps will stretch over and value to zero. Considering the stride value is usually small, value, and gets the dot product to construct feature maps. Each channel is represented by a particular matrix with the pixel value range from 0 to 255. Another matrix called the ground. On the other hand, if UA Vs are flying aerially, caused by the propeller unbalance, especially when the rotation speed, thus this approach could avoid the damage of audio as input data to detect the damaged propellers. The spectrograms are generated by four propellers’ rotation in different scenarios based on the spectrogram and CNN. The audio signals generated by four propellers’ rotation in different scenarios are converted to 2D images. The CNN treats spectrograms of audio as input data to detect the damaged propellers.

B. Image classification test

Fig. 9 presents the framework of the experimental test based on the spectrogram and CNN. The audio signals generated by four propellers’ rotation in different scenarios are converted to 2D images. The CNN treats spectrograms of audio as input data to detect the damaged propellers. Fig. 10 shows the training progress of CNN. The total 160 spectrogram images are comprised of 80 images from the broken propeller and 80 images from the unbroken propeller, and lay in two different files, respectively. The Matlab code randomly selects 50 images from each file to compose the training data (100 images), and randomly selects 15 images from each file to compose the validation data (30 images). The remaining images make up the test data (30 images). Since there are only two kinds of outputs, the classification accuracy begins around 50%. After the network training, the classification from the neural network is extremely efficient and accurate, and the test data accuracy can be 96.67%. All the spectrograms are collected in the different propeller rotation speed, thus this approach could avoid the damage caused by the propeller unbalance, especially when the rotation speed is relatively low and UA Vs have not taken off from the ground. On the other hand, if UA Vs are flying aerially, the fault detection can allow UA Vs to take measurements quickly and escape some further damages.

V. Generalized Diagnostic Model for UAVs

A. CNN-based transfer learning technique

The CNN with the spectrogram has a striking performance on the UAV propeller fault diagnosis. Given different UAVs have various characteristics, like the propeller size, the frame of the UAV, the propeller rotation speed and so on, it’s not universal to apply a well-trained neural network on all kinds of UAVs. Therefore, each UAV has to develop its own neural network to detect failures. However, numerous training data requirement is one of the essential properties of the neural network, which constrains the generalization of
this fault diagnosis approach. Thus, this paper implements a method called transfer learning to transfer the knowledge from a well-trained UAV model to a new UAV model with insufficient data. The definition of transfer learning refers to the work from Pan and Yang (2010) [34]. Pan and Yang introduced two conceptions called domain and task. For the domain, it is denoted as $D$ and comprised of a feature space $X$ and a marginal probability distribution $P(x)$. For the task, it is denoted as $T$ and comprised of a label space $y$ and an objective predictive function $f(\cdot)$ that is written as $P(y|x)$. Transfer learning utilizes the knowledge ground on a source domain $D_S$ and learning task $T_S$ to improve the target predictive function $f(\cdot)$ performance of a learning task $T_T$ in a target domain $D_T$, where $D_S \neq D_T$, $T_S \neq T_T$.

B. Transfer learning experimental test and improvement

Fig. 11 shows the framework of transfer learning experimental test. The abundant audio training data from the first quadrotor is employed by CNN to set up a well-trained network. The Matlab code utilizes most network layers and isolates the last few layers of the network, and replaces them by new layers that learn specific features based on the spectrograms of audio from the second quadrotor. The transfer learning only needs a few training data from the second quadrotor, and fine-tunes the weights of each layer during the training progress. The spectrogram images with the same total number are collected from the second quadrotor. As this paper mentioned before, the classification accuracy of the first quadrotor is 96.67%. We apply all the spectrogram images collected from the second quadrotor as test data on the well-trained diagnostic network model. The classification accuracy without transfer learning is 55.00% which almost corresponds to the proportion of the propeller types. To improve the generalization of the fault diagnostic model, the Matlab code randomly selects 5 spectrogram images from

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The structure of CNN

![Diagram of CNN structure](image)

Fig. 8: The structure of CNN

The structure of the experimental test to train and validate CNN

![Diagram of experimental test](image)

Fig. 9: The structure of the experimental test to train and validate CNN

The training and validating of the CNN

![Graph showing training and validation accuracy](image)

Fig. 10: The training and validating of the CNN

Transfer learning framework

![Diagram of transfer learning framework](image)

Fig. 11: Transfer learning framework
the broken and unbroken propeller files, respectively. The 10 spectrogram images compose the training data of the transfer learning progress. The validation data is still made up by 30 spectrogram images. The remaining 120 spectrogram images are the test data. Fig. 12 indicates the training progress, and the classification accuracy of the test data from the second quadrotor is 81.67% which is much higher than 55.00%. To increase the classification accuracy, we modify the number of training spectrogram images to be 20. The validation data is still made up by 30 spectrogram images. The remaining 110 spectrogram images are the test data. Fig. 13 indicates the training progress of transfer learning with 20 training images, and the classification accuracy is 91.82%. Hence, as different quadrotors, even though the parameters of quadrotors are various, the audio-based fault diagnosis model still shows a promising accuracy (91.82%).

![Accuracy(%)](image)

**Fig. 12:** The training progress based on transfer learning with 10 training images

![Accuracy(%)](image)

**Fig. 13:** The training progress based on transfer learning with 20 training images

VI. Conclusions

This paper presents a new fault diagnostic method for the physical damage of the propellers used on quadrotor UAVs. The method only needs the audio data from the quadrotor’s flight and does not require the physical model of the quadrotor. This diagnostic model is first developed based on the CNN, which is trained by labeled data gathered from quadrotors with different damaged propellers. The model is then generalized by transfer learning, such that the model trained by the data from one quadrotor can be applied to another quadrotor without too much additional training. One advantage of this method is that it is only based on the audio data which is very easy to obtain. The audio data is converted to the 2D spectrogram and sent to the CNN in terms of images. Experimental studies have been conducted to validate the effectiveness of the proposed fault diagnostic model.

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