Acoustic non-destructive testing of UAS´s propellers during pre-departure and post-flight checks

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Abstract

Unmanned Aerial System (UAS) activities have increased steeply in the last years, market research forecasts a continuous increase in the near future. The rapid growth of this industry, however, has outpaced the development of rules and systems to govern their use, as well as those to ensure a safe operation before, during and after flight. Maintenance, Repair and Overhaul (MRO) aspects will gain relevance as more and more UAS take to the sky.

Rotary-wing UAS have 2 or more propellers, which are easily damaged during normal operation of the vehicle. The reduced thrust and increased vibration imply losing performance and setting the UAS structure under stress. With the propellers being the main source of sound of the propulsion system, we propose the use of acoustics to identify damaged propellers. Microphones placed off-board do neither disrupt UAS operation nor reduce the payload capacity. Furthermore, this method does not depend on a particular manufacturer or software.

In this paper, we present a concept for the non-destructive testing of multi-copter propellers. The fault diagnosis aims at recognizing the difference in sound between damaged and undamaged propellers. This evaluation takes place before the UAS takes off the ground and after it lands, thus allowing to interrupt a possible dangerous mission or identifying damage occurred during operation. The vehicle is on the ground in an "idle state" where the propellers already spin, but not fast enough to lift it. This state is used for a first analysis of the sound of a single propeller and several propellers, as well as for the generation of data. Next, two approaches for the detection of damage are developed and their performance is evaluated: an analytical approach and a machine learning algorithm based on an autoencoder neural network.

1. Introduction

Beyond Visual Line of Sight (BVLOS) flights refer to UAS operations where the vehicle flies outside of the normal visible range of the pilot. They provide numerous advantages compared to normal UAS operations, but they are still strongly limited due to the current European Union Aviation Safety Agency (EASA) regulations. Yet, the total BVLOS global market is expected to increase by over 70% between 2021 and 2026. (*1*)

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In order to facilitate autonomous BVLOS operations and in particular remote overhaul services, new vertiport concepts with integrated fault diagnose activities are presented in (*2*). Acoustic monitoring is proposed as a universal inspection technology while the vehicle is still on the vertiport. It allows near real-time monitoring, does not penalize payload due to additional sensors and is easily integrated into a vertiport.

2. Background

In the previous work (*3*), the authors explored the possibility of detecting a damaged propeller on an experimental setup consisting of a single propeller. The impact of the rotational speed of the propeller and the relative position between propeller and microphone were also evaluated. In this paper, the object of interest is a full UAS with its 4 propellers attached to it. A similar approach can also be found in Bondyra (*4*), Iannace (*5*), and Liu (*6*). Bondyra et al. use propellers with fractured tips and edge distortions, MFCC-based features and two approaches: a convolutional and a LSTM-based neural network (NN), both achieving F1 metrics above 98%. This is a good performance; however, their recording method is not applicable for the described use-case due to the additional weight, as they place the microphone array directly on the UAS. Iannace et al. aim to detect unbalanced propellers, which are taped to create the imbalance. They use the linear sound pressure instead of the MFCC, and he evaluation of the model, a convolutional NN, provides an accuracy of 97%. This is also not the focus of the current work, as the damage of interest are not slightly unbalance propellers but damaged tips, as they have a bigger impact on the vehicle performance. Liu et al., who also use a CNN, provide the spectrogram as input data to detect damaged propellers where the tip has been cut off. There is no information about the microphone used and the amount of training data is quite small (160 images), the accuracy obtained is 97%.

3. Methodology

This chapter describes the experimental setup for the acquisition of data, an analysis of the obtained data and the approach taken to detect damage.

3.1 Experimental set-up

The experimental set-up consisted of a quadcopter, a Holybro X500, placed between two microphones (Oktava MK-012) in a semi-anechoic chamber, see *Figure 1*. The propellers mounted on the Holybro were two-bladed propellers (1045 V2) and the considered damages were broken tips, namely 5mm, 10mm, 20mm and 30mm being cut of one of the tips of one of the propellers (this corresponds to approx. 2%, 4%, 8% and 12% of the length of the propeller being cut off). For clarity reason, propellers are referred to from this point on as $\boldsymbol{prop_{und}}$ (undamaged), $\boldsymbol{prop_{05}}$ (5mm cut), $\boldsymbol{prop_{10}}$ (10mm cut), $\boldsymbol{prop_{20}}$ (20mm cut), $\boldsymbol{prop_{30}}$ (30mm cut). Two microphones, on opposite sides of the quadcopter, are used to guarantee that the propellers on both sides are recorded equally, as the orientation and the position of the microphone has a big impact on the recordings. A single microphone above the Holybro was not an option, as it is problematic in a real take-off phase, and a microphone below it is too much affected by the downwash of the propellers.

The considered rotational speed of the propellers, $\boldsymbol{f_{rot}}$, is within the standard range in an arming phase, namely 8% of the maximum rotational speed of the motors. In this case, it corresponds approximately to 1080 rpm or 18 Hz.
First, recordings are taken of a single propeller in both undamaged and damaged states varying through the mounting position of all four propulsion motors. These recordings are done with the microphone which is nearest to the moving propeller in each case. Next, recordings of all 4 propellers in an undamaged state are taken. Finally, recordings of 4 propellers, where one propeller is damaged and the other 3 are not, are performed.
These two recording options (each propeller separately or all propellers simultaneously) correspond to two possible test routines before and/or after a flight: *TR I* and *TR II*.

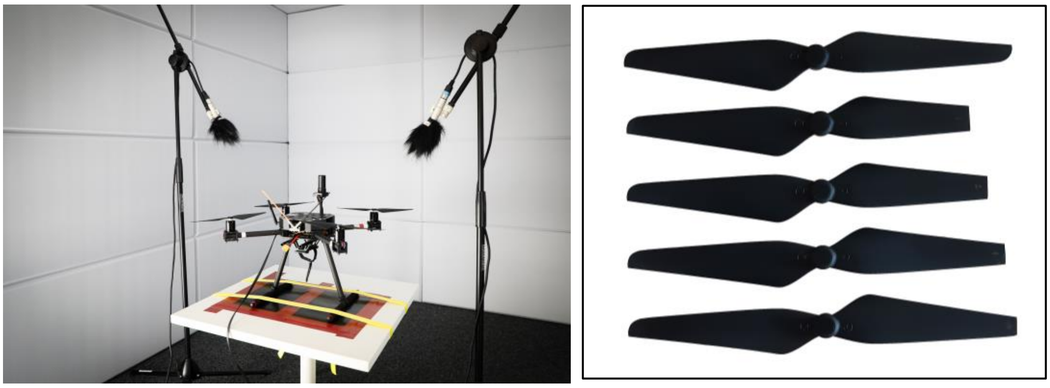

Figure 1. Set-up for data acquisition inside a semi-anechoic chamber (left) and image of propellers used for the recordings (right). From top to bottom: undamaged, 30mm, 20mm, 10mm, and 5mm cut.

3.2 Data description

The result of the recordings is a dataset with the following characteristics:

- Audio sampling frequency: 44100 Hz
- Bit-depth: 32-bit floating point format
- Number of recording sessions: 2
- Rotational speed of the propellers, $\boldsymbol{f_{rot}}$: 8% of maximum speed, approx. 18 Hz
- Total number of samples (see **Table** 1)

Table 1. Total length of recordings (seconds) of a single propeller (test routine I) and 4 simultaneously turning propellers (test routine II).

Single propeller (*TR I*)			**4 simultaneous propellers (*TR II*)**	
$\boldsymbol{prop_{und}}$	2215		4 $\boldsymbol{prop_{und}}$	998
$\boldsymbol{prop_{30}}$	465		3 $\boldsymbol{prop_{und}}$ and 1 $\boldsymbol{prop_{30}}$	464
$\boldsymbol{prop_{20}}$	465		3 $\boldsymbol{prop_{und}}$ and 1 $\boldsymbol{prop_{20}}$	464
$\boldsymbol{prop_{10}}$	464		3 $\boldsymbol{prop_{und}}$ and 1 $\boldsymbol{prop_{10}}$	464
$\boldsymbol{prop_{05}}$	465		3 $\boldsymbol{prop_{und}}$ and 1 $\boldsymbol{prop_{05}}$	464

3.3 Damage detection

Based on the recorded data, two approaches for the damage detection are implemented and compared: an analytical approach and a machine learning approach.

3.3.1 Analytical approach

An analysis of the data shows that the frequency content of the sound of an undamaged propeller has a clear peak at the blade passing frequency (BPF), which in this case corresponds to $\boldsymbol{f_{BPF} = 2 * f_{rot}}$ due to the two blades of each propeller. For damaged propellers, a peak can also be seen clearly at $\boldsymbol{f_{rot}}$. The analytical approach is based on a comparison between the rate of these two frequency components, namely at $\boldsymbol{f_{rot} = 18Hz}$ and at $\boldsymbol{f_{BPF} = 36Hz}$. The greater the damage, the bigger the ratio $\boldsymbol{f_{18Hz}/f_{36Hz}}$.

80% of the recordings from the undamaged propellers are chosen randomly and the threshold to divide recordings from damaged or undamaged propellers is calculated by the interquartile range rule, where Q_1 is the first quartile and Q_3 the third quartile (*7*):

$$\boldsymbol{threshold = 1.5 * (Q_3 - Q_1) + Q_3} \quad (1)$$

In the case of two microphones being considered, if either of the channels is classified as damaged, the recording is classified as damaged.

3.3.2 Machine learning approach: the autoencoder

An autoencoder is a neural network which is trained to copy its input to its output. Internally, it consists of an encoder and a decoder, which are designed so that they are unable to create perfect reconstructions. In this way, the model learns to prioritize the defining properties of the data. If everything works as it should, the reconstructions from the "correct" data will have a low reconstruction error, while the reconstructions from the "incorrect" data will have a higher one (*8*). The threshold is also chosen via the interquartile rule shown in the previous section, and if either of the channels is classified as damaged, the recording is classified as damaged.

4. Experiments and results

4.1 Analytical and autoencoder implementation

The analytical approach is implemented in a python script where the audio recordings are divided into 1-second audio snippets, the frequency content (periodogram) is calculated to obtain the $\boldsymbol{f_{18Hz}/f_{36Hz}}$ ratio for each audio sample and the threshold to divide between normal values and outliers is calculated using a random 80% of the samples. The other 20% is used for evaluation.

For the autoencoder, the power spectral density (PSD) is calculated out of the 1-second audio snippets. Exploratory data analysis shows that the addition or exclusion of the highest frequencies does not have an impact on the performance of the autoencoder. Therefore, just the frequencies up to 4.4kHz are considered for further evaluation; this reduces the input size and evaluation time of the network. The autoencoder itself is implemented and trained using TensorFlow (*9*). It consists of a 2-layer encoder (32 and 16 neurons) and 2-layer decoder (32 neurons and output layer). For each training process, the data available is divided into a training set (70% of normal recordings), a validation set (20% of $\boldsymbol{prop_{und}}$ and 50% from $\boldsymbol{prop_{30}}$), and a test set (10% of $\boldsymbol{prop_{und}}$ and 50% from $\boldsymbol{prop_{30}}$). The model is then also evaluated for the 20mm, 10mm and 5mm cut recordings. The network is training with a learning rate of 0.001 and an Adam optimizer. An early stopping is used to monitor the validation loss and stop the training if it has not improved at least 10^{-5} in 8 epochs.

4.2 Evaluation of performance

The following table shows the results of the single propeller evaluation for both the analytical approach and the autoencoder approach.

Table 2. Accuracy results of analytical approach and autoencoder for single propeller evaluation (*TR I*)

Single propeller	**Analytical approach**	**Autoencoder**
$\boldsymbol{prop_{und}}$	86%	95%
$\boldsymbol{prop_{30}}$	100%	100%
$\boldsymbol{prop_{20}}$	100%	100%
$\boldsymbol{prop_{10}}$	100%	100%
$\boldsymbol{prop_{05}}$	100%	88%
F1-score	**0.98**	**0.98**

Next, the results of the evaluation of the recordings of all propellers turning at the same time are described. For the purpose of completeness, the performance when considering the nearest and the furthest microphone to the damage is specified (or right and left microphone for the $\boldsymbol{prop_{und}}$ case), as well as the overall performance when considering both microphones.

Table 3. Accuracy results of analytical approach and autoencoder for 4-turning-propellers evaluation (*TR II*)

	Analytical approach			**Autoencoder**		
	Nearest mic.	**Furthest mic.**	**Combined**	**Nearest mic.**	**Furthest mic.**	**Combined**
4 $\boldsymbol{prop_{und}}$	93% *	89% *	**84%**	94% *	100% *	**94%**
3 $\boldsymbol{prop_{und}}$ and 1 $\boldsymbol{prop_{30}}$	100%	25%	**100%**	100%	100%	**100%**
3 $\boldsymbol{prop_{und}}$ *and 1* $\boldsymbol{prop_{20}}$	100%	16%	**100%**	84%	77%	**89%**
3 $\boldsymbol{prop_{und}}$ *and 1* $\boldsymbol{prop_{10}}$	79%	13%	**82%**	52%	45%	**62%**
3 $\boldsymbol{prop_{und}}$ *and 1* $\boldsymbol{prop_{05}}$	28%	11%	**36%**	61%	54%	**69%**
F1-score	**0.88**			**0.89**		

** Nearest and furthest correspond to the right and left microphones in case of all* $\boldsymbol{prop_{und}}$.

The analytical approach for single propellers has a very good performance detecting damaged propellers, 100%, but also 14% of false positives. The autoencoder for this same case has just 5% of false positives and the same results for the damaged cases except for $\mathbf{prop_{05}}$, which is a 12% worse.

Both approaches for the simultaneously turning propellers present in general a worse performance. The analytical approach has an accuracy of 84% for $\mathbf{prop_{und}}$, which means 16% false positives. It detects all damages above 20mm, over 80% of $\mathbf{prop_{10}}$, but just 36% of $\mathbf{prop_{05}}$. The autoencoder has a 94% accuracy for $\mathbf{prop_{und}}$ and 100% for $\mathbf{prop_{30}}$. The performance for $\mathbf{prop_{20}}$ and $\mathbf{prop_{10}}$ are 89% and 62%, which is worse than the analytical approach (100% and 82%), but for $\mathbf{prop_{05}}$ is better (69% vs. 36%).

5. Conclusion

This work presents two algorithms for the evaluation of UAS propellers' health condition using acoustic emissions during two test routines. Considered are damaged two-bladed propellers with one broken tip. First, an analytical approach focuses on the ratio between the rotational speed of the motor and the blade passing frequency, and a threshold value is obtained using the interquartile rule. Second, an autoencoder neural network is implemented with TensorFlow and its threshold is also calculated with the interquartile rule. Both approaches are evaluated for recordings of single propellers and of simultaneously turning propellers. Based on the obtained results, the best accuracy is obtained for propellers recorded separately. Both the autoencoder and the analytical approach obtained a F1-score equal to 0.98. The autoencoder is able to detect all damages greater than 10 mm with a percentage of false alarms of 5%, but misses some of the smaller damages. The analytical approach detects all damages greater than 5 mm but has a false alarm rate of 14%. This means a sequential test routine before or after a flight where all propellers are recorded separately (called test routine I in this work), has the best chances of detecting damages, but the choice of algorithm will be based on the trade-off between false alarm rate and the detection of smaller damages. However, if time is a limiting factor, choosing test routine II is also an option, as satisfying results can be achieved using less than a quarter of the time for the check (F1-score 0.89). During the outdoor operation, the acoustic monitoring system is exposed to ambient noise and gusts of wind, which impact the quality of the recorded data. Future work should concentrate on solutions like filtering algorithms and include the integration of the test routines in a vertiport so that the evaluation is performed automatically.

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