Vibration Anomaly Indicator in UAVs in presence of Wind

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One of the critical factors affecting flight safety of unmanned aerial vehicles (UAVs) is the amount of vibration they are exposed during a flight. For UAVs under remote operation, vehicle stabilization and navigation is typically achieved by estimating its attitude and position using onboard miniature sensors such as accelerometers, gyroscopes, and GPS via an onboard autopilot. Since precise control of the UAV relies heavily on the attitude sensing, the vibration levels need to be as low as possible in order to minimize the signal noise. Incorrect sensor data can lead to uncertain state estimation causing the multirotor to drift from its desired position. Moreover, high vibrations can induce faults in the safety-critical components of the UAV such as its on-board sensors, motors and propellers. Hence, it is important to monitor the vibration levels during a UAV flight. This paper specifically looks into effect of wind on the vibrations recorded by the autopilot system in an octocopter. Using data from experimental flights under varying wind conditions, we aim to classify between a nominal and anomalous vibration level and define a safety metric known as the Vibrational Anomaly Indicator (VAI) for small UAV systems. Further, we will study effect of high vibrations on the inertial measurement unit (IMU) of an octocopter under laboratory set-up and compute the VAI from IMU measurements. Results would demonstrate the utility of VAI as an health indicator for unmanned flights either in presence of winds or from degraded on-board IMU sensor.

I. Motivation and Related Work

Unmanned Aerial Vehicles (UAVs) are becoming increasingly common in aerospace applications, including aerial photography, surveillance, package delivery and precision agriculture. While the potential for smaller aircraft offers numerous benefits, unique challenges often arise with UAV flight safety. Larger manned aircrafts typically incorporate numerous redundancies in their monitoring and control systems to ensure safety, but UAVs are restricted by their size and weight. Therefore, it is critical to develop effective health monitoring systems for UAVs, as backup systems are often not an option for these aircraft. Fault detection and diagnosis is a valuable approach to health monitoring for these aircraft,and can be applied to a variety of components to assess the state of the aircraft and determine a need for maintenance or even flight termination [1, 2].

Over the last several years, fault detection and diagnosis through the analysis of vibration signals from UAVs has become an increasingly popular area of study [3, 4]. Applications of such analysis can range from diagnosing or predicting specific failure modes, such as bearing faults [5], propeller damage and friction [3, 6], excessive payload [4], to simply determining the optimal location for instrument placement to minimize the effects of nominal vibrations [7]. Frequency analysis is a common approach to understanding vibration signals originating from rotating parts, such as the motors and propellers in aircraft, especially for fault analysis, as it can reveal features in the frequency domain that arise as a result of changes in the usual periodic behavior of these components [4]. There are a wide variety of approaches to frequency analysis, including the classical Fourier transform as well as the newer wavelet decomposition and variations on each of these in an effort to resolve issues with loss of time information and cross-term interference [8–10]. However, one of the key challenges that we face in our UAV application is low data sampling rate from on-board autopilot systems which limits our capability of obtaining key frequency domain features from the UAV vibration data that can reasonably

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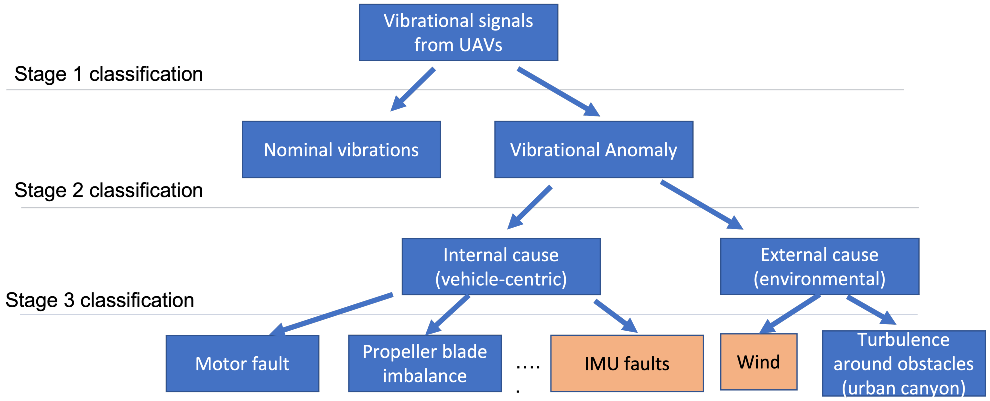


Fig. 1 Vibrational Anomaly Detection and classification for a UAV- concept flowchart.

detect any anomaly. We intend to repeat some of the aforementioned analysis and report their performance on our data, given the low sampling rate.

When looking at a vibration signal to extract information on vehicle health, we propose a three stage classification system, shown in Figure 1. Upon measuring the vibration signal, the first stage of classification is to determine if the vibration is a nominal vibration resulting from expected sources in the aircraft such as its rotating components, or if it is an anomaly that affect flight safety. If the vibration is classified as an anomaly, the second stage is to determine if the cause is internal or external to the aircraft. When the anomaly is due to a fault with the aircraft, the third and final stage would be to isolate the anomaly source such as motor failure, propeller imbalances or IMU degradation. However, before attempting to diagnose a fault within the aircraft, causes external to the system should be eliminated. Therefore, of particular interest in this study is determining when anomalies are due to external factors, specifically wind. An additional interest to identify the source of vibrational anomalies is that decision making post anomaly detection depends on the source. For example, if a UAV is operated on a wildfire monitoring zone with high wind and high temperature environment and it experiences vibrations caused due to the external factors, it needs to be re-routed or re-planned accordingly. On the other hand, if vibrations arise from a vehicle-centric fault, the UAV operation may needs to be terminated, either taken out for repair or replacement. Hence it is important to study the effect of both external and internal factors on UAV vibrations. In this paper, we focus on studying the effect of wind on vibrations measured by on-board sensors on the UAV. In section VII. we would throw some light on our recent IMU degradation studies caused by vibrations and compare those with nominal IMU measurements.

II. Failure Mode and Effect Analysis of Vibrations in UAVs

This section will focus on the various sources of vibrational anomalies, their causes (vehicle-centric or environmental), likelihood of such anomalies in UAV flights and severity of failures caused by vibration.

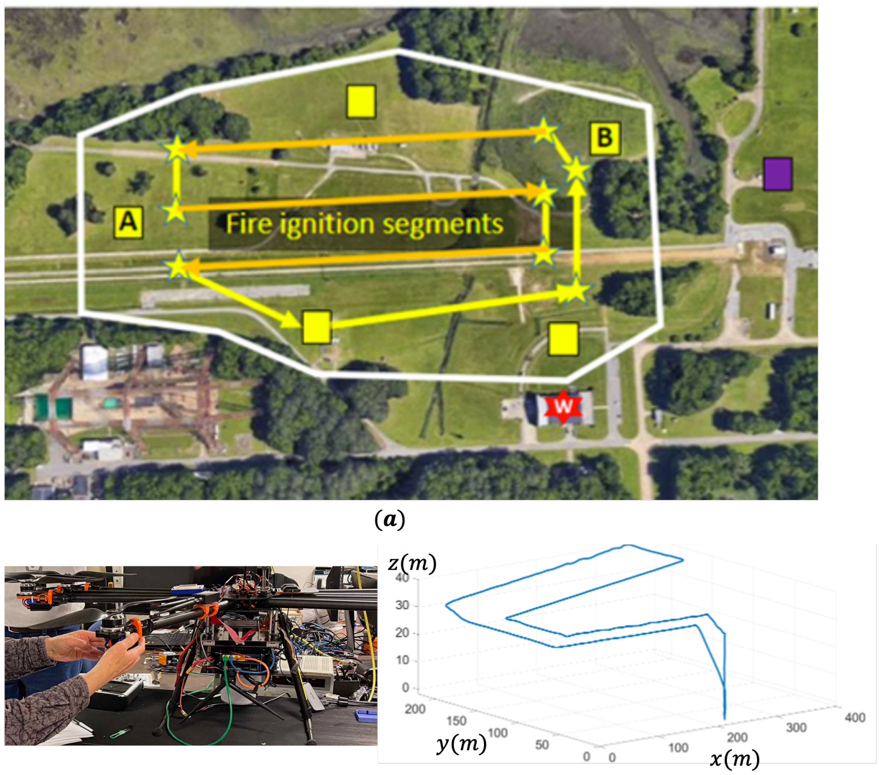
III. Vibrational Anomaly Indicator for UAV flights

This section will define a metric known as the Vibrational Anomaly Indicator that computes the severity of a vibration recorded by an on-board sensor in the UAV. The vibrations computed for a UAV flight which had to be terminated due to high turbulence will be considered as a reference of "Severe Vibrations". Vibration measurements recorded from other flights at varying wind conditions will be assessed in comparison to this reference.

IV. Vibration data from UAV flight experiments

In this section, we summarize the data used in this study, based on UAV flight experiments conducted at NASA Langley Research Center [11]. The data for this study was collected during four flight tests using an octocopter Tarot in autonomous mode, equipped with Pixhawk hardware and controlled with Ardupilot software. Figure 2(b) shows the aircraft used for this study.

Data collected by the aircraft include aircraft status, such as power drawn, position and heading information, IMU



(b) (c)

Fig. 2 (a) Flight plan at NASA Langley Research Center (b) Tarot octocopter installed with Ardupilot vibrational sensors (c) Flight trajectory followed by a UAV in x-y-z coordinates.

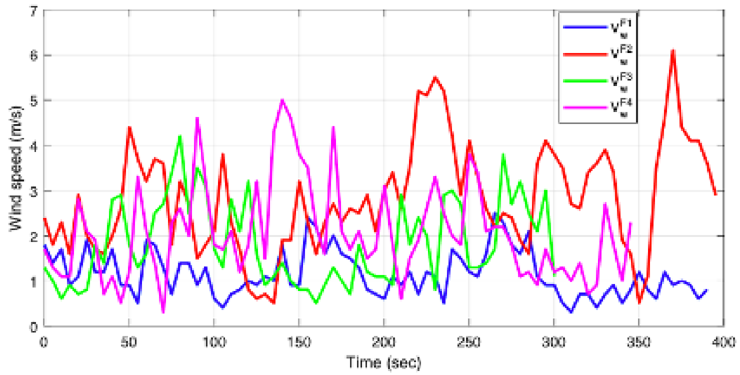


Fig. 3 Wind data recorded for the four flight times F1- F4.

data from an accelerometer and gyroscope, and vibration data. All data obtained from the aircraft was sampled at a rate of 2Hz. We note that these sensors are all located at the center of the aircraft, and sensor data for the individual motors is not available. All four test flights followed the same flight plan as shown in Figure 2(a). The trajectory followed by a UAV with 9 waypoints is shown in Figure 2(c).

The flights had the following UAV ground speed and wind speed profiles:

- Flt 41:low ground speed (5m/s) with mostly low wind speeds (<2.5m/s)
- Flt 43:low ground speed (5m/s) with mostly high wind speeds (<6m/s)
- Flt 44:high ground speed (8m/s) with mostly high wind speeds (<5m/s)
- Flt 45:high and low ground speeds (8m/s and 3m/s during final segment of flight) with mostly high wind speeds (<4.5m/s)

The wind speed data was collected by a Centralized PI Controller located within 100m of the flight path, and was sampled once every 5s. The location of the wind sensor is denoted as the red start in figure 3 (a). This data also included the heading of the wind, and we note that no information for a vertical component is included. The effects of surrounding trees and building is considered to be negligible. The wind speeds for each flight are shown in Figure .

The vibration data was collected for the x,y, and z axes of the aircraft, where the x and y axes are parallel to the body of the aircraft and the x axis points toward the front of the aircraft; the z axis then represents the vertical components. As previously mentioned, this data was collected at a rate of 2Hz. Collection began a few minutes prior to flight and concluded about a minute after flight. The data was trimmed to only include the time window of interest. This time frame was determined based on when the z axis acceleration showed significant increase, indicating take off, and concluded when these values stopped changing, indicating landing.

A. Initial Observations from Vibration Measurements

The vibration magnitudes computed from the three axes for flights F1, F2 and F4 are shown in Figure 4. The corresponding histograms of the vibration data along the three separate axis are shown in Figure 5. From the above figures, it can be deduced that wind magnitude has an effect on the overall vibration magnitude, i.e. with higher winds, the UAV recorded higher vibration levels. The variance in the vibration measurements stays the same for all wind conditions, which is assumed to be more of a characterization of the sensor itself irrespective of the wind it encounters.

The other important observation that was noted from these flight experiments is that vibrations encountered by a UAV depends on its air speed in addition to the wind speed. Figure 6 shows the corresponding ground speed profile for the four flights, as measured by the on-board navigation sensors. Figure 6 compares flights F1 and F2 whereas Figure 6(b) compared flights F3 and F4. The highlighted section of Figure 6(a) indicates higher vibration levels for high wind scenario, given both flights have the same UAV ground speed profile. On the other hand, in Figure 6(b), the highlighted section indicates that for similar wind speed, vibrations recorded by a UAV flying at a higher speed is higher compared to a low-speed UAV. The reason could be that a UAV flying at a higher speed demands higher rotor speed and if there's a propeller imbalance or the vehicle frame imbalance, overall vibrations get more pronounced, compared to a low-speed UAV.

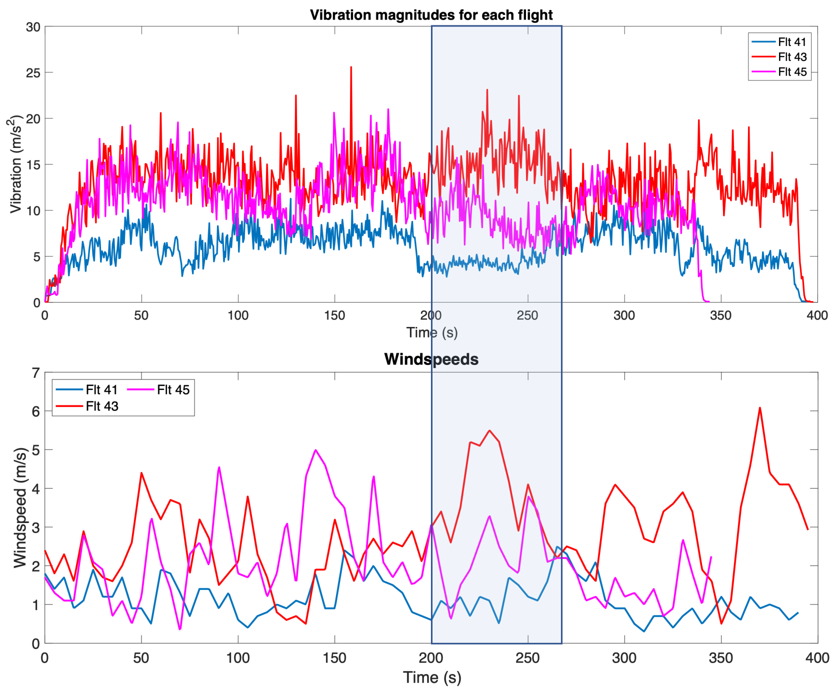


Fig. 4 (a) Vibration magnitudes (b) Corresponding wind profiles for flights F1 (Flt 41), F2 (Flt 43) and F4 (Flt 45).

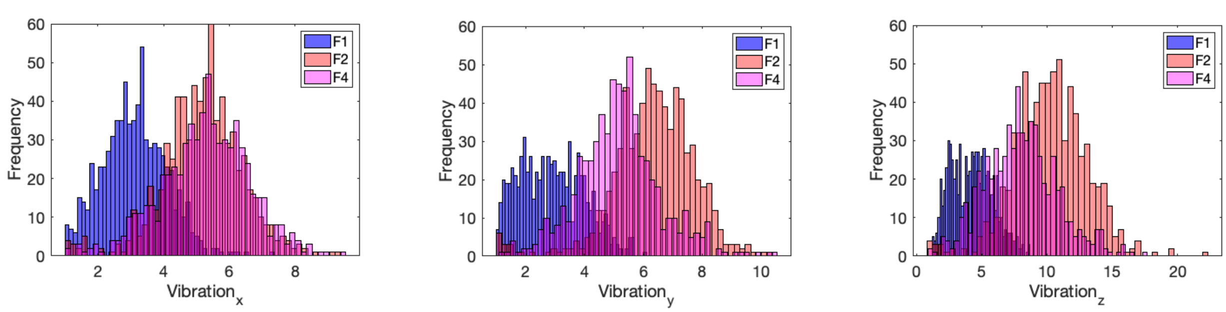
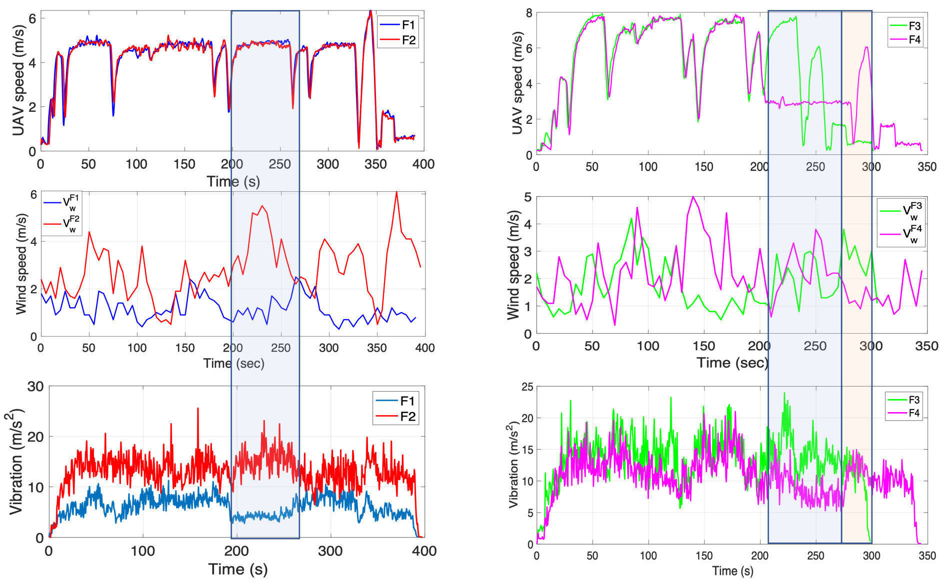


Fig. 5 Histogram of vibration data for Flight F1, F2 ans F3 along (a) x-axis, (b) y-axis and (c) z-axis.



(a) (b)

Fig. 6 Vibrations corresponding to UAV ground speed and wind speed for (a) Flights F1 and F2 and (b) Flights F3 and F4.

V. Additional analysis on the Experimental Vibrational data

VI. Computation of Vibrational Anomaly Indicator for experimental flights

VII. Vibrations due to IMU degradation

This section will focus on the effects of IMU degradation on data integrity by examining IMU-specific failure modes consistent with high vibration environments. Supported by laboratory-based experimentation, IMU performance will be compared with two identical IMUs, a new IMU, and an IMU exposed to long duration high frequency vibration. The experimental setup relies on a Beaglebone Black, a small single-board embedded computer, to perform data acquisition from two LSM9DS1 Accelerometers from ST, affixed to a laboratory shake plate capable of producing variable frequency vibration.

VIII. Conclusion

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References

[1] Palanisamy, R. P., Kulkarni, C. S., Corbetta, M., and Banerjee, P., "Fault detection and Performance Monitoring of Propellers in Electric UAV," *2022 IEEE Aerospace Conference (AERO)*, IEEE, 2022, pp. 1–6.

[2] Banerjee, P., Corbetta, M., and Jarvis, K., "Probability of Obstacle Collision for UAVs in presence of Wind," *AIAA AVIATION 2022 Forum*, 2022, p. 3460.

[3] Al-Badour, F., Sunar, M., and Cheded, L., "Vibration analysis of rotating machinery using time–frequency analysis and wavelet techniques," *Mechanical Systems and Signal Processing*, Vol. 25, No. 6, 2011, pp. 2083–2101.

[4] Bektash, O., and la Cour-Harbo, A., "Vibration analysis for anomaly detection in unmanned aircraft," *ANNUAL CONFERENCE OF THE PROGNOSTICS AND HEALTH MANAGEMENT SOCIETY 2020*, PHM Society, 2020.

[5] Banerjee, P., Okolo, W. A., and Moore, A. J., "In-flight detection of vibration anomalies in unmanned aerial vehicles," *Journal of Nondestructive Evaluation, Diagnostics and Prognostics of Engineering Systems*, Vol. 3, No. 4, 2020.

[6] Bondyra, A., Gasior, P., Gardecki, S., and Kasiński, A., "Fault diagnosis and condition monitoring of UAV rotor using signal processing," *2017 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA)*, IEEE, 2017, pp. 233–238.

[7] Verbeke, J., and Debruyne, S., "Vibration analysis of a UAV multirotor frame," *Proceedings of isma 2016 international conference on noise and vibration engineering*, 2016, pp. 2401–2409.

[8] Feng, Z., Liang, M., and Chu, F., "Recent advances in time–frequency analysis methods for machinery fault diagnosis: A review with application examples," *Mechanical Systems and Signal Processing*, Vol. 38, No. 1, 2013, pp. 165–205.

[9] Neild, S., McFadden, P., and Williams, M., "A review of time-frequency methods for structural vibration analysis," *Engineering Structures*, Vol. 25, No. 6, 2003, pp. 713–728.

[10] Romberg, T., Cassar, A., and Harris, R., "A comparison of traditional Fourier and maximum entropy spectral methods for vibration analysis," 1984.

[11] Young, S. D., Ancel, E., Dill, E. T., Moore, A., Quach, C. C., Smalling, K. M., and Ellis, K. K., "Flight Testing In-Time Safety Assurance Technologies for UAS Operations," *AIAA Aviation 2022 Forum*, 2022, p. 3458.