



IN-FLIGHT VIBRATION SIGNAL BASED DETECTION AND LOCALIZATION FOR UAV PROPELLER ANOMALIES UNDER UNCERTAINTY VIA MACHINE LEARNING TYPE METHODS

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Abstract

The problems of in-flight vibration-based detection and localization of early-stage anomalies in propellers of Unmanned Aerial Vehicles (UAV) that operate under uncertainties have been investigated. In-flight UAV propeller anomaly detection is achieved via two unsupervised machine learning type methods, that operate within a Multiple Model (MM) framework and rely on data-driven stochastic non-parametric and parametric models for the UAV dynamics representation, estimated from vibration signals from a single accelerometer. The first, referred to as U-MM-PSD employs the Welch-based Power Spectral Density (PSD) estimates as dynamic-informed and sensitive to propeller anomaly features, while the second, abbreviated as U-MM-AR, the AutoRegressive (AR) parameter vectors, respectively. On the other hand, the in-flight UAV propeller anomaly localization is tackled via the two supervised versions of the aforementioned methods, referred to as MM-PSD and MM-AR. The methods' performance is assessed using vibration signal measurements from the PADRE data repository that have been obtained from a quadcopter vehicle operating under unknown conditions and uncertainties. These measurements correspond to the UAV under nominal state and under four anomalies pertaining to a propeller with a chipped edge located on a different rotor each time. The results indicate almost excellent anomaly detection and localization performance of both MM based methods, with the one employing Welch based PSD estimates achieving the highest correct detection rates for all propeller anomalies and the highest (98.12%) correct localization score. Finally, a comparison with the typical One-Class Support Vector Machine (OCSVM) and k-Nearest Neighbors (kNN) machine learning techniques has also been conducted, confirming the superiority of the postulated MM based methods.¹

Keywords: UAV anomaly detection, UAV anomaly localization, in-flight vibration signals, Multiple Model methods

1. Introduction

In the rapidly evolving field of unmanned aerial vehicle (UAV) technology, ensuring the structural integrity and operational reliability of components such as propellers is paramount. Propellers play a vital role in the rotary-wing UAV's stability and maneuverability, therefore structural anomalies (defects) in their blades, such as surface damages, deformations, imbalances, and so on, may lead to catastrophic failures during flight, endangering civilian lives and causing damage to property. Such anomalies may occur during UAV normal operation primarily due to harsh operating conditions and demanding mission requirements. Therefore, vibration-based anomaly detection and localization for UAV propellers is of paramount importance, as it is expected to ensure the UAV's safe operation and reliable performance in various missions and applications [1], without necessitating the disruption of

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UAV normal operation. The basic principle upon which vibration-based anomaly detection and localization methods are founded is that any propeller anomaly induces changes in the UAV dynamics which are, in turn, reflected in the measured random vibration signals and their characteristics.

Vibration-based anomaly detection and localization via machine learning type methods constitute practical approaches for the structural integrity assessment of UAV propellers, using a reasonable amount of historical vibration response signals without the need for physics-based models that may not represent accurately the UAV dynamics [2]. In addition, they may allow for specific adjustments and targeted repairs in the affected rotor, avoiding thus the entire UAV overhaul and leading to enhanced preventive maintenance and optimized UAV designs and protocols, significantly boosting operational longevity and effectiveness.

Studies within the context of vibration-based anomaly detection via machine learning type methods, rely mostly on Neural Networks (NNs) [3, 4, 5, 6, 7, 8, 9, 10] and Support Vector Machines (SVMs) [11, 12]. The employed features in these methods mostly consist of static quantities extracted from the vibration response signals in the time domain [3], such as the RMS, skewness and kurtosis that provide gross UAV dynamics information due to their low dimensionality. Other NN-based methods rely on certain spectrum-related amplitudes and frequency bandwidths in the frequency domain [4], requiring the type of effects of the considered propeller anomaly on the vibration response spectrum to be a-priori known. Most of the aforementioned methods achieve high anomaly detection performance under different operating conditions and uncertainties (such as different flying altitudes, trajectories, speeds, and environmental conditions), yet they operate in a supervised manner [13, 14, 15, 16, 12, 9, 8, 5] requiring vibration signals from the UAV with propeller anomaly for their training, which may not be feasible in some applications. This supervised approach may be attributed to the fact that the selected features obtained from the in-flight UAV vibration signals, such as the RMS or targeted frequency bandwidths, are not sensitive to propeller anomalies and, perhaps, are affected by operating conditions and uncertainties, thus the employed models need to recognize specific complex patterns between the features corresponding to the nominal and the anomalous UAV propellers. In addition, the inherent lack of transparency on the decision-making process of the NN based methods, as well as the need for a large number of vibration signals from a single [8] or multiple sensors [10] for their training, may compromise their applicability in critical applications [15, 6].

On the other hand, studies within vibration-based localization via machine learning methods focus on the determination of which UAV rotor exhibits propeller anomaly via Support Vector Machines (SVMs) [11] and Random Decision Forests [15] and rely on static, scalar, frequency domain features, such as the average vibration response spectrum amplitude within a narrow frequency bandwidth, requiring a large number of vibration signals for their training in order to discriminate the propeller anomaly location effectively. Other methods rely on the discrimination of changes in the vibration response spectrum [13, 14] due to the different locations of the UAV propeller anomalies. Such methods rely on more dynamics-informed feature vectors, and in particular on the Fast Fourier Transform amplitudes of wider frequency bandwidths, thus the changes due to the different propeller anomaly locations may be effectively reflected [13, 14]. However, their effectiveness requires prior knowledge of the different location effects on the vibration response spectrum, and the operating condition levels (speed, altitude, trajectory) to be known, thus limiting their adaptability and automation. Furthermore, it should be noted that the methods described above focus on severe UAV propeller anomalies, such as cracks or totally broken blades, with obvious effects on the vibration signals.

The *goal* of the present study is to investigate and address the problems of vibration-based detection and localization for UAV propeller anomalies occurring at a single rotor using vibration measurements from a single sensor. This is to be achieved under three main requirements: (a) achievement of high propeller anomaly detection and localization performance, (b) robust detection and localization under unknown uncertainties affecting the in-flight measurements, and (c) the use of limited instrumentation and simple, interpretable decision procedures for the UAV state.

The sub-problem of vibration-based anomaly detection is presently tackled via two unsupervised machine learning type methods that operate within a Multiple Model framework. These rely on data-driven stochastic non-parametric and parametric models for the partial representation of the

UAV dynamics as “viewed” by the employed sensor. The Multiple Models of the first unsupervised method consist of Welch-based estimates of the vibration response Power Spectral Density (PSD), thus this method is referred to as U-MM-PSD, whereas the second incorporates Multiple AutoRegressive Models, and is abbreviated as U-MM-AR. The sub-problem of vibration-based anomaly localization is tackled via the supervised versions of the aforementioned methods, which, for easy distinction from their unsupervised counterparts, are referred to as MM-PSD and MM-AR, respectively. The Welch-based PSD estimates are chosen to constitute the feature (also known as characteristic quantity) of the U-MM-PSD and MM-PSD, whereas the AR model parameter vector is the feature of the U-MM-AR and MM-AR ones.

The performance of the postulated methods for anomaly detection and localization is assessed using in-flight vibration signal measurements from the PADRE data repository that have been obtained from a quadcopter vehicle moving under unknown operating conditions and uncertainties. The employed signals in this study correspond to the UAV under nominal state and under four propeller anomalies of the same type (chipped edge propeller) located on a different rotor each time.

UAV propeller anomaly detection and localization consist of two phases, the baseline and inspection phase, and involve the detection of changes in each method’s feature (pseudo-sufficient statistics) using hypothesis testing between in-flight vibration signals obtained during the two phases. In particular, the baseline (off-line) phase of UAV propeller anomaly detection methods is based on in-flight signals collected from a UAV in a nominal state without propeller anomalies, whereas the inspection (on-line) phase on a fresh in-flight vibration signal corresponding to the UAV of unknown state (unknown propeller condition). On the other hand, UAV propeller anomaly localization methods operate within a classification framework with the baseline phase relying on vibration signals from the UAV with propeller anomaly on specific, known, locations (rotors), and the inspection phase on a fresh in-flight vibration signal from the UAV of with propeller anomaly at an unknown location (rotor).

Beyond introducing the aforementioned framework and methods, the study offers a number of additional features and unique characteristics, including the following:

- Performance assessment for each of the MM based methods under unknown operating uncertainty, using a minimal number of vibration signals from a single accelerometer.
- Accurate detection and localization of early-stage UAV propeller anomalies, the effects of which on the UAV dynamics are masked by the operating uncertainties via unsupervised and supervised versions of the postulated MM based methods, respectively.
- Detection and localization of early-stage UAV propeller anomalies rely on unique dynamic feature vectors that, compared to gross characteristics such as the RMS, or certain spectrum frequencies it is sensitive to the subtle effects caused to the UAV dynamics by the different propeller anomaly location, and additionally may separate them from corresponding effects due to the unknown operating uncertainties.
- Performance comparisons with conventional machine learning methods for detection and localization of UAV propellers anomalies.

2. Operating Frameworks

This section delineates the way the sub-problems of anomaly detection and anomaly localization for UAV propellers are treated, including all necessary prerequisites for the presented methods’ proper training and real-time operation using vibration signals from a single accelerometer mounted on a UAV that operates under unknown uncertainty levels (speed, position, route, wind speed).

In-flight anomaly detection for UAV propellers

The problem of in-flight vibration based anomaly detection for UAV propellers is treated in an unsupervised manner which is precisely stated as follows:

Given:

- *Baseline phase:* This is the training phase of the method which is performed once, using n measurements of random vibration acceleration signals, say $y_i[t]$ ($i = 1, \dots, n$) with t designating

the normalized discrete time, each obtained from the “nominal” UAV consisting of nominal UAV propellers without any structural anomaly (or fault).

- *Inspection (on-line) phase*: This phase is performed in real-time once the baseline phase has been completed, using a new acceleration signal $y_u[t]$ from the same sensor location used in the baseline phase, corresponding to unknown (subscript ‘u’ designates unknown) UAV propeller condition and, in turn, the unknown UAV health state.

Determine: if the condition of the UAV propellers is similar or not to that of the nominal ones and, in turn, if the UAV state is “nominal” or not.

In-flight UAV propeller anomaly localization

The problem of in-flight vibration-based anomaly localization for UAV propellers constitutes an extension of the previous sub-problem and is treated separately in a supervised manner. This is precisely stated as follows:

Given:

- *Baseline phase*: It is formulated once and off-line based on n random N -sample long vibration response signals per propeller anomaly location j associated with a UAV rotor, that are denoted as $y_i^j[t]$ ($i = 1, \dots, n$ and $j = 1, \dots, m$ with m designating the overall number of rotors).
- *Inspection phase*: It is performed in real-time (on-line) using exclusively a fresh response signal, $y_u[t]$, from the same sensor location as in the baseline phase under *unknown* propeller anomaly location or else rotor location; the subscript “u” designates the unknown propeller anomaly location.

Determine: the propeller anomaly location that is in which rotor the propeller anomaly occurs.

Remarks: In-flight anomaly detection and anomaly localization for UAV propellers are presently achieved in batch mode. In this sense, batches of short-duration vibration signals that may be obtained during the UAV’s normal operation in a periodic mode or on-demand are used in the postulated method, while the final decision-making is performed at the end of a data batch. Furthermore, the former operates in an unsupervised manner, whereas the latter is supervised. Finally, they may be performed either successively or individually, depending on the specific requirements of the UAV operation and the objectives of the monitoring process.

3. The dataset, the propeller anomalies and preliminary analysis

3.1 The PADRE dataset

In the present study, the anomaly detection and anomaly localization for UAV propellers is based on vibration signals from the recently introduced PADRE database [17]. This expanding, publicly accessible repository contains sensor-generated data from flight sessions across different multicopter propeller anomalies. Raw vibration signals, obtained from 4 accelerometers and 4 gyroscopes positioned close to the UAV propellers are available. Thus, for each one of the 8 sensors, measurements from three dimensions are obtained, providing thus a total of 24 vibration signals unprocessed signals. The vibration signals are obtained with a sampling frequency of $f_s = 500$ Hz. Details on the experimental procedure may be found in [17].

3.2 The propeller anomalies, propeller anomaly locations and the employed vibration signals

The considered anomalies in the UAV in the present study are sourced from the PADRE data repository [17] and pertain to a propeller with chipped edge that occurs in various rotor configurations, affecting thus one, two, three, or four rotors according to the dataset description in [17]. Since the main aim of the present study is the detection and localization of early-stage propeller anomalies, the single-rotor configuration is employed in order to highlight and address the significant challenges posed by early-stage UAV propeller anomalies due to their subtle nature and minimal impact on the

Table 1 – Details on the UAV health states and the vibration signals

UAV state	No. of available signals
Nominal propellers (0000)	13
Single Chipped Edge propeller (F1000; F0100; F0010; F0001)	52 (13 per anomaly location)
'0': healthy propeller, '1': indicating which of A;B;C;D rotors has a chipped edge (Fig.1) Sampling frequency: 500 Hz; signal length: 6 144 samples (12.29 s)	

UAV dynamics, often making them indistinguishable from normal operation variability and uncertainties. In addition, these are to be achieved using vibration signals from a single sensor, without requiring redundant instrumentation that may affect the flight performance, maneuverability, and energy efficiency of the UAV [8]. Therefore, only the vibration signals from the vertically sensing accelerometer on the second rotor (rotor B) of the Bebop 2 drone are used. An indicative schematic with the accelerometer location in the UAV is shown in Fig. 1. The employed acceleration signals have been obtained with the UAV operating under a "nominal" state with nominal propellers (no propeller anomaly) and under 4 individual anomalous states pertaining to a propeller with a chipped edge located in each of the four UAV rotors. The details on the UAV states and the pertinent notations are summarized in Table 1.

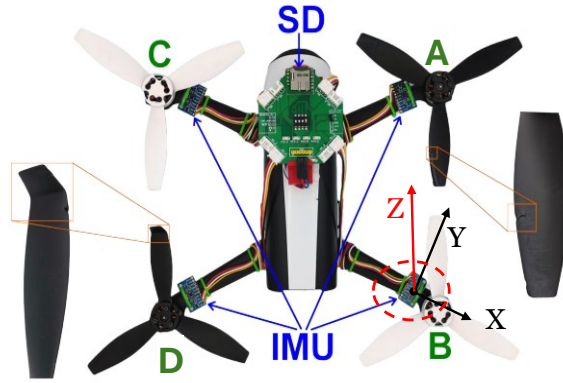


Figure 1 – Bebop 2 drone schematic [17].

3.3 Effects of the structural propeller anomalies and unknown operating uncertainties on the vibration signals and the UAV dynamics

The effects of anomaly pertaining to the chipped edge propeller and the unknown operating uncertainties on the acceleration signals and the UAV dynamics are explored in this section. The UAV dynamics are primarily represented via the Welch-based estimates of the Power Spectral Density (PSD) using only the vibration signals from the single accelerometer on rotor B of the UAV (refer to subsection 3.2).

In particular, Fig. 2 depicts indicative Welch-based PSD estimates (Hamming window length = 1 024 samples, Overlap = 95%, frequency resolution: $\delta f = 0.5$ Hz) corresponding to the UAV with no propeller anomalies and with a chipped edge propeller on rotor A. Each PSD envelope shows the overall effect of the unknown operating uncertainties on the UAV dynamics under the nominal and anomalous state, indicated with blue and grey tint, respectively. Based on this, it is evident that the PSD envelopes are significantly overlapped among them throughout the whole frequency bandwidth, implying that the UAV dynamics under nominal and anomalous states are not clearly discriminated due to uncertainty, thus confirming that the sub-problem of propeller anomaly detection is highly challenging as expected.

In addition, the effects of propeller anomaly location and the unknown operating uncertainties on the UAV dynamics are illustrated in Fig. 3 through indicative Welch-based PSD envelopes corresponding

to single chipped edge fault located in two different rotors, rotor A and rotor C. These envelopes demonstrate that the operating uncertainties significantly impact the UAV dynamics, "masking" the effects corresponding to different propeller anomaly locations, rendering thus the sub-problem of propeller anomaly localization particularly challenging.

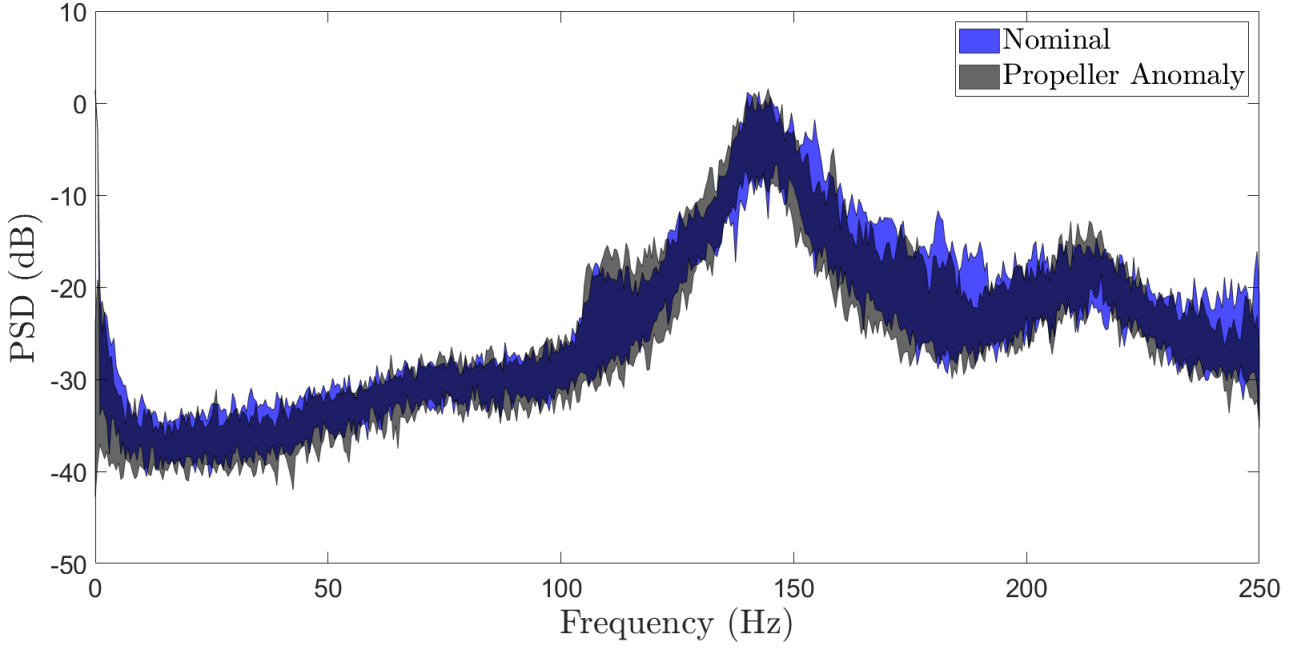


Figure 2 – Effects of the unknown operating uncertainties on the UAV dynamics under the nominal (no propeller anomalies) and anomalous (chipped edge propeller) state via Welch-based PSD envelopes: [13 vibration signals per UAV state are used in each plot.]

4. The employed machine learning type methods for UAV propeller anomaly detection and localization

4.1 Description of the Multiple Model (MM) framework

The machine learning type methods for tackling the sub-problems of UAV propeller anomaly detection and localization operate within an Multiple Model (MM) framework [18], and rely on either nonparametric or parametric data-based representations of the partial UAV dynamics. In particular, two MM based methods that operate in an unsupervised manner are employed for UAV propeller anomaly detection. The first method, abbreviated as U-MM-PSD, employs the Welch-based PSD estimates, whereas the second, referred to as U-MM-AR, relies on AutoRegressive (AR) models. The supervised versions of these methods are employed for UAV propeller anomaly localization, which, for distinction, are abbreviated as MM-PSD and MM-AR, respectively. The steps of the employed MM based methods are presented individually for each sub-problem in the following sections.

4.1.1 Steps of the unsupervised Multiple Model methods for UAV propeller anomaly detection

The two unsupervised MM based methods, U-MM-PSD and U-MM-AR, for the sub-problem of UAV propeller anomaly detection consist of two steps that are concisely described in the sequel:

Step 1. Baseline (training) phase: This includes the formulation of the MM representation of the healthy UAV dynamics (no propeller anomaly), designated as $\mathbb{M}_o$, that consists of a set of individual data-based representations per method (Welch based PSD estimates and AR models) each designated as $M_{o,i}$ ($i = 1, \dots, n$) with n standing for the $\mathbb{M}_o$ dimensionality) and estimated based on a vibration signal obtained from UAV under nominal state.

Step 2. Inspection phase: In this step, the propeller anomaly detection is performed, and the current unknown UAV state is determined as nominal or not. Thus, a similar model as those used in the baseline phase, designated as M_u , is estimated based on fresh vibration signal obtained from the

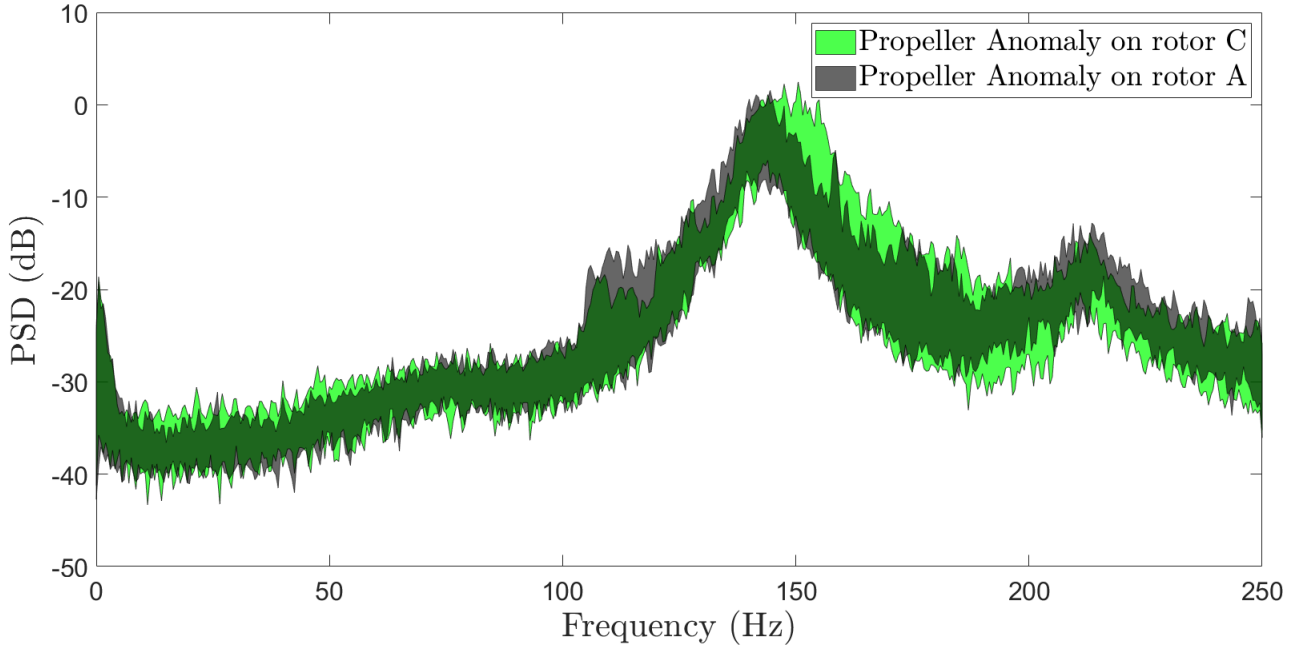


Figure 3 – Effects of the unknown operating uncertainties on the UAV dynamics under two anomalous states (propeller anomaly located on rotors A and C) via Welch-based PSD envelopes. [13 vibration signals per UAV state are used in each plot.]

same sensor location as in the baseline phase under unknown propeller condition and thus UAV health state. Then, the detection of the UAV propeller anomalies is based on determining whether or not the current model M_u belongs to the MM representation $\mathbb{M}_o$. In the positive case where no anomalies are detected, the propellers and, in turn, the UAV are declared as nominal, whereas in the negative case, the propeller exhibits anomalies, thus the UAV is declared as not nominal (anomalous). The decision-making mechanism is then based on a distance metric S between the current model M_u and $\mathbb{M}_o$. This is currently defined as the minimum of individual distances between M_u and all components of $\mathbb{M}_o$, that is:

$$S := \min_i d(M_{o,i}, M_u), \quad \text{for } i = 1, \dots, n \quad (1)$$

with $d(M_{o,i}, M_u)$ designating a statistical distance between the two individual models $M_{o,i}$ and M_u . For the MM-PSD method, the Euclidean distance is employed, which is defined as:

$$d(M_{o,i}, M_u) = \sqrt{(\hat{\mathbf{p}}_{o,i} - \hat{\mathbf{p}}_u)^T (\hat{\mathbf{p}}_{o,i} - \hat{\mathbf{p}}_u)} \quad (2)$$

with $\hat{\mathbf{p}}_{o,i}$ and $\hat{\mathbf{p}}_u$ constituting the method's feature vector and designating the Welch based PSD estimates corresponding to $M_{o,i}$ and M_u models, respectively. On the other hand, the MM-AR method is based on the following Mahalanobis distance:

$$d(M_{o,i}, M_u) = \sqrt{(\hat{\boldsymbol{\theta}}_{o,i} - \hat{\boldsymbol{\theta}}_u)^T (\hat{\mathbf{P}}_{o,i})^{-1} (\hat{\boldsymbol{\theta}}_{o,i} - \hat{\boldsymbol{\theta}}_u)} \quad (3)$$

with $\hat{\boldsymbol{\theta}}_{o,i}$ and $\hat{\boldsymbol{\theta}}_u$ constituting the method's feature and standing for the estimated AR parameter vectors associated with $M_{o,i}$ and M_u models, respectively, while $\hat{\mathbf{P}}_{o,i}$ designates the estimated covariance matrix of $\hat{\boldsymbol{\theta}}_{o,i}$.

4.1.2 Steps of the supervised Multiple Model methods for UAV propeller anomaly localization

The steps of two supervised methods, MM-PSD and MM-AR, for the sub-problem of UAV propeller anomaly localization are concisely described in the sequel:

Step 1. Baseline (training) phase: This includes the formulation of m MM representations of the UAV dynamics under chipped-edge propeller anomaly with m standing for the overall UAV rotors number (herein $m = 4$). Thus, each MM representation corresponds to a specific rotor indicating a propeller anomaly location under the unknown operating uncertainties and is designated as $\mathbb{M}_j$ ($j = 1, 2, \dots, m$) with the subscript “ j ” indicating the j -th propeller anomaly location (rotor). Each $\mathbb{M}_j$ representation consists of a set of models denoted as M_i^j for $i = 1, 2, \dots, m$ and $i = 1, 2, \dots, n$ (n designating each $\mathbb{M}_j$ dimensionality), estimated from the vibration response signals $y_i^j[t]$ (refer to section 2.).

Step 2. Inspection phase: This step includes the localization of the chipped edge propeller. Thus, a current model, designated as M_u (the subscript “ u ” designates unknown propeller anomaly location), estimated from a fresh response signal $y_u[t]$ (see section 2.). Then, localization is achieved by classifying the M_u to one of the $\mathbb{M}_j$ MM representations of the baseline phase. The decision-making mechanism is based on a distance metric D_j between the current model M_u and each $\mathbb{M}_j$. This is currently defined as the minimum of individual distances between M_u and all components of $\mathbb{M}_j$, that is:

$$D := \min_j D_j \quad \text{for } i = 1, 2, \dots, n \quad (4)$$

with $D_j = \min_i d(M_i^j, M_u)$ for $j = 1, 2, \dots, m$ and $d(M_i^j, M_u)$ designating a statistical distance between the two individual models. The employed statistical distances are the same as those described in section 4.1.1, thus are omitted for space conservation.

The vibration response PSDs that are utilized in the MM-PSD method for the representation of the UAV dynamics are estimated via the Welch method (*Matlab function: pwe1ch.m*). For the MM-AR method, all models are estimated via Ordinary Least Squares (OLS) [19, pp. 81–83] *Matlab function: ar.m*, while model order selection is based on the Bayesian Information Criterion (BIC) and the Residual Sum of Squares normalized by the Signal Sum of Squares (RSS/SSS) [19, pp. 505–507], and model validation on typical model residual whiteness examination [19, pp. 512–513].

5. Performance assessment

5.1 The assessment procedure

The methods’ performance assessment for the UAV propeller anomaly detection and localization is based on an iterative “rotation” approach, akin to S-fold cross-validation [20, p. 33], which prevents biased results from specific vibration signals used in training, thus ensuring statistically reliable method evaluations and comparisons. For the sub-problem of propeller anomaly detection, a certain number of vibration signals corresponding to the UAV healthy state are randomly selected in each “rotation” for the training of MM based methods, while the rest signals are used in the inspection phase. This procedure is repeated until all available signals are included in the training phase at least once. The same process is applied for the methods’ performance assessment in the sub-problem of propeller anomaly localization, with the difference that, an equal number of vibration signals are now randomly chosen from each UAV propeller anomaly location for the training phase, while the remaining are utilized in the inspection phase.

The study utilizes 20 rotations for the methods’ performance assessment, leading to 80 inspection test cases per UAV state (Nominal, F0001, F0010, F0100 and F1000) and thus to a total of 400 and 320 inspection test cases for the sub-problems of propeller anomaly detection and anomaly localization respectively; see more details in Table 2.

5.2 UAV propeller anomaly detection results and comparisons

Step 1. Baseline phase: $n = 9$ response signals are employed per rotation for the construction of the MM representation $\mathbb{M}_o$ representing the nominal UAV dynamics under unknown operating uncertainties. Thus, the MM representation consists of $n = 9$ Welch based PSD estimates for the U-MM-PSD and $n = 9$ conventional AR(164) models for the U-MM-AR method. The details on the estimation of the vibration response PSD and the AR models are presented in Table 3.

Step 2. Inspection phase: The vibration response signal $y_u[t]$ from each of the 400 test cases of the inspection phase (see Table 2) is considered to be obtained under unknown UAV propeller conditions and a single model M_u , either Welch-based PSD or AR model is estimated and then employed in the

Table 2 – Details on the methods S-fold assessment procedure for both propeller anomaly detection and localization sub-problems.

No. of Rotations	Nominal State	Propeller Anomaly			
		F1000 Rotor A	F0100 Rotor B	F0010 Rotor C	F0001 Rotor D
Baseline (training) phase					
1	9	9 ^b	9 ^b	9 ^b	9 ^b
20	180	180	180	180	180
Inspection phase					
1	4 ^a	4	4	4	4
20	80	80	80	80	80

^a Only used in propeller anomaly detection; 400 inspection signals^b Only used in propeller anomaly localization; 320 inspection signals

Table 3 – Details on the MM based methods for both propeller anomaly detection and localization sub-problems.

Method	Models	Feature vector dimensionality	Distance type
U-MM-AR / MM-AR	AR(164)	164	Mahalanobis
U-MM-PSD / MM-PSD	Welch based PSD	1024	Euclidean
<i>Baseline (training) phase</i>			
Multiple Model (MM) dimensionality:			
U-MM-AR / U-MM-PSD: $\mathbb{M}_o$ dimensionality $n = 9$ (see section 4.1.1)			
MM-AR / MM-PSD: $\mathbb{M}_j$ dimensionality $n = 9$ for j -th anomaly location ($j = 1, \dots, 4$) (section 4.1.2)			
<i>Inspection phase</i>			
U-MM-AR / U-MM-PSD: <i>Anomaly detection</i> based on step 2 in section 4.1.1.			
MM-AR / MM-PSD: <i>Anomaly localization</i> based on step 2 in section 4.1.2.			
<u>AR model</u> : Estimation via OLS [19, p. 204], <i>Matlab function</i> : <code>ar.m</code> , selected model AR(164); BIC: -1.62 ; SPP: 37; Condition Number: 8.24×10^2			
<u>Welch based PSD</u> : Estimation via <i>Matlab function</i> : <code>pwelch.m</code> ; Hanning window length = 1 024 samples; Overlap = 0.95%; frequency resolution: $\delta f = 0.49$ Hz			

pertinent MM based method for propeller anomaly detection (see details in Table 3 and also refer to section 4.1.1). The anomaly detection results for the U-MM-PSD method are presented in Fig. 4 in terms of scatter plots of the method's distance metric S and Receiver Operating Characteristic (ROC) curves for all test cases. Specifically, the S distance metric values corresponding to the nominal state of the UAV are clearly discriminated from those associated with the propeller anomalies F0001, F0010, and F0100 and slightly overlapped with those from F1000, indicating almost perfect anomaly detection performance through the U-MM-PSD method. This effectiveness is also confirmed by the corresponding ROC curves, which indicate a 100% correct detection rate (True Positive Rate, TPR) and 0% false alarms (False Positive Rate, FPR) for the propeller anomalies F0001, F0100, and F1000 and 88.75% correct detection rate for F0010.

Similarly, Figure 5 displays the distance metric S and Receiver Operating Characteristic (ROC) curves from the U-MM-AR method, which exhibits slightly lower detection performance as it reaches a lower 57% correct detection rate for the propeller anomaly F1000, compared to the 88.75% achieved by the U-MM-PSD method. However, the U-MM-AR method performance in detecting the propeller anomalies F0001, F0010, and F0100 is also excellent reaching 100% correct detection and 0% false alarms.

A critical comparison with two variants based on the One-Class Support Vector Machine (OCSVM) classifier [21] that has been widely used [11] is also conducted following the same assessment procedure as described in section 5.1. The OCSVM classifier (*Matlab function*: `ocsvm.m`; Standardize-

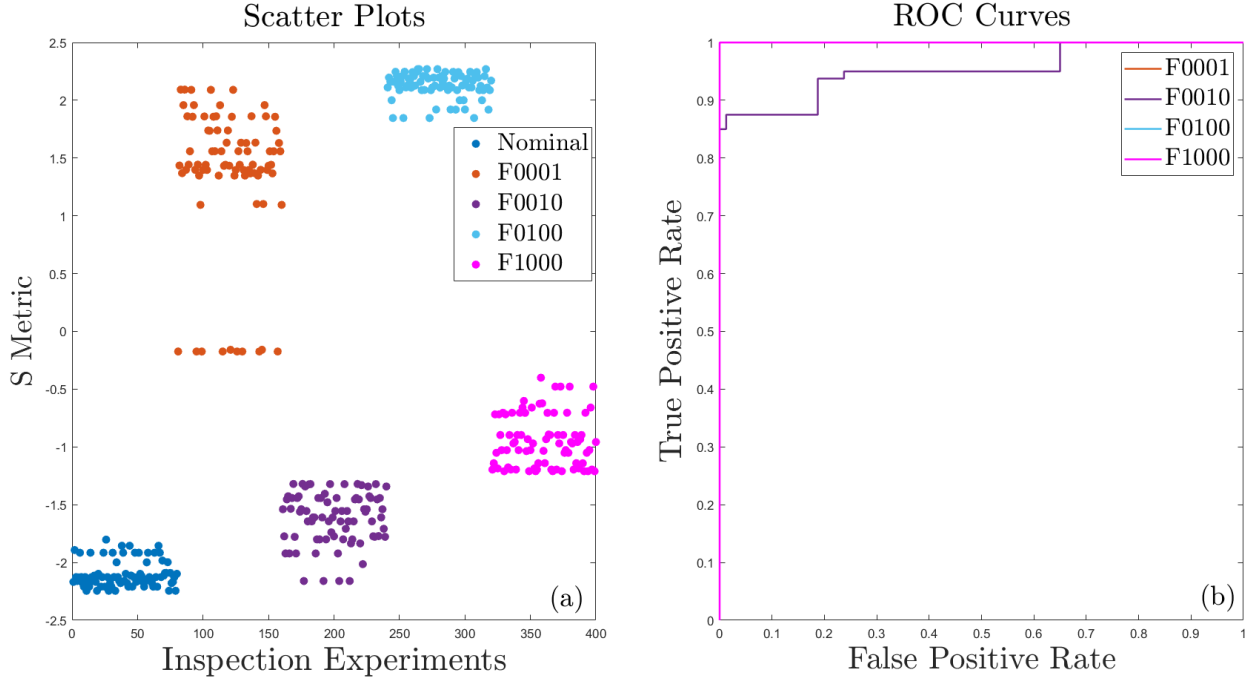


Figure 4 – Propeller anomaly detection performance assessment of the U-MM-PSD method in terms of scatter plots of the distance metric S (a) and ROC curves (b). [80 inspection test cases per anomalous state (400 in total)].

Data=true; KernelScale="auto") is trained with the Welch PSD estimates and the parameter vector of the AR models, thus leading to two OCSVM variants, a non-parametric (OCSVM-PSD) and a parametric one (OCSVM-AR), for a fair comparison with the respective MM based methods. Figure 6 summarizes the Area Under the Curve (AUC) values as obtained from the MM based methods and the OCSVM variants for all inspection test cases. It is clear, that the MM based methods achieve almost excellent performance, as pointed out in 5.2, whereas the performance of the corresponding OCSVM variants is good but inferior. In particular, the performance of the OCSVM-PSD is high, with the corresponding AUC values reaching 100% correct detection rate, yet failing to detect the propeller anomaly F0010. Conversely, the highest AUC value of the OCSVM-AR variant peaks at 78% correct detection rate, with significantly inferior performance compared to the PSD variant and its MM based counterparts.

5.3 UAV propeller anomaly localization results based on the MM Framework and comparisons

Baseline phase: $n = 4$ response signals are employed for the construction of each MM representation $\mathbb{M}_j$ (Welch based PSD estimates and conventional AR(164) for MM-PSD and MM-AR, respectively) representing the dynamics of the UAV under unknown uncertainty and a single early-stage propeller anomaly located at the j -th rotor as described in section 4. Thus, each j -th MM representation consists of $n = 4$ Welch-based PSD estimates and AR(164) models for the MM-PSD and MM-AR methods, respectively. The details on the estimation of the vibration response PSD and the AR models are summarized in Table 3.

Inspection phase: The vibration response signal $y_u[t]$ from each of the 320 inspection test cases of the inspection phase (see Table 2) is considered to be obtained under unknown propeller anomaly location and it is driven through the two MM based methods.

To facilitate a direct comparison for the MM based methods, the widely used machine learning technique, k-Nearest Neighbors (k-NN), has been employed [22]. The k-NN method (*Matlab function*: `fitcknn.m`; search method: Exhaustive; no. of nearest neighbours: $K = 2$; BreakTies: Nearest; Weight: Equal) is trained using Welch PSD estimates and the parameter vector of the AR models, resulting in two variants: a non-parametric (k-NN-PSD) and a parametric (k-NN-AR). Both MM and

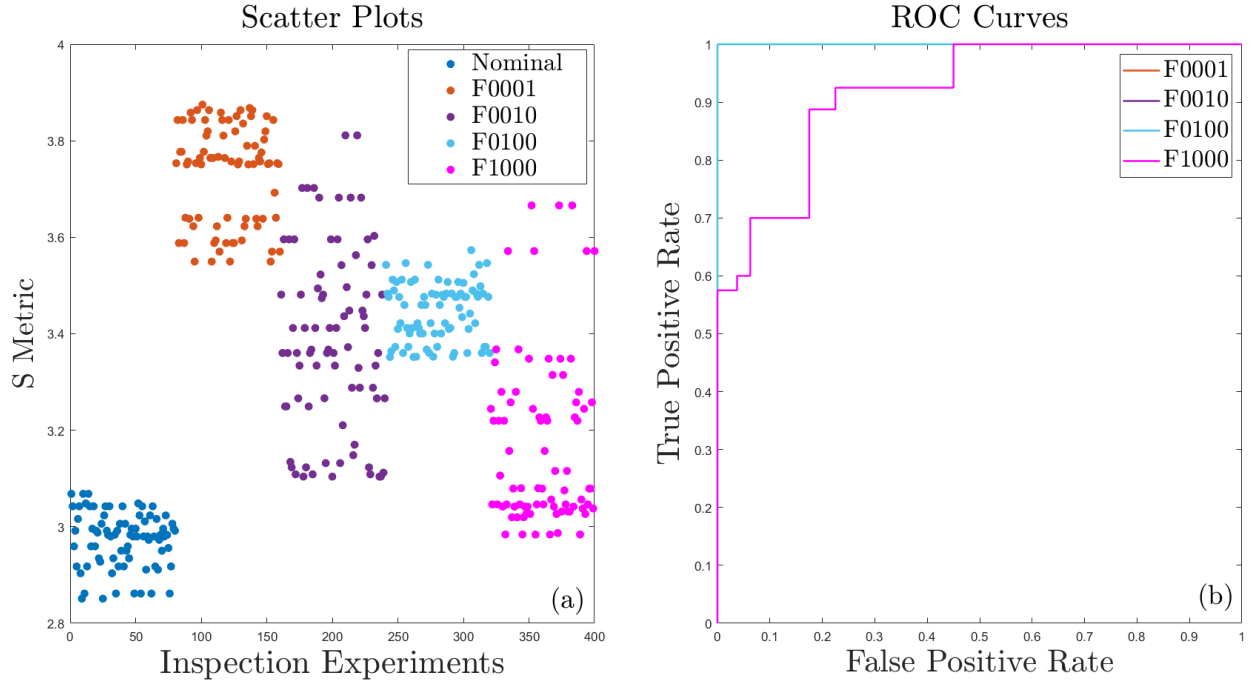


Figure 5 – Propeller anomaly detection performance assessment of the U-MM-AR method in terms of scatter plots of the distance metric S (a) and ROC curves (b). [80 inspection test cases per anomalous state (400 in total)].

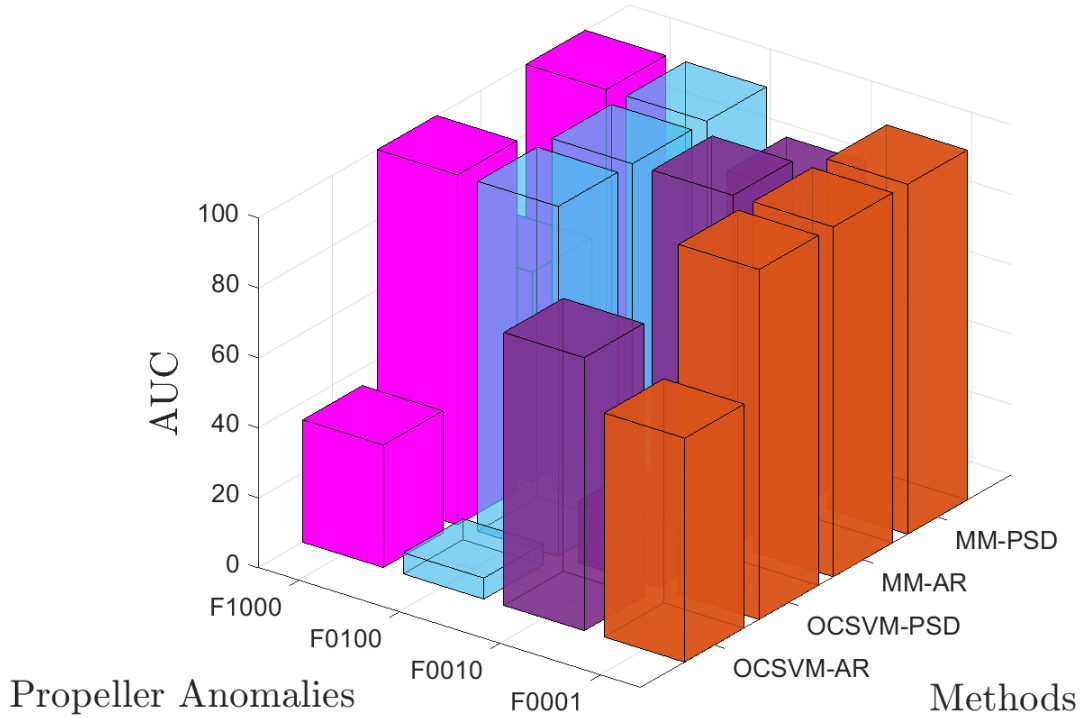


Figure 6 – Comparison of the unsupervised MM based methods (U-MM-AR, U-MM-PSD) for anomaly detection with their respective OCSVM counterparts (OCSVM-AR, OCSVM-PSD) in terms of AUC values [80 inspection test cases per anomalous state (F0001; F0010; F0100; F1000), 400 in total per method].

k-NN based methods employ the same S-fold assessment process detailed in section 5.1. It is important to note that for the k-NN-PSD and k-NN-AR methods, Euclidean and Mahalanobis distance metrics have been utilized, respectively, allowing for a meaningful comparison with the MM based

methods.

The results for the MM based and the k-NN based methods are presented through the corresponding confusion matrices displayed in Fig. 7. Each column of the confusion matrix in the upper left 4×4 submatrix corresponds to the actual location of propeller anomaly, with each row representing the predicted anomaly location. The i,j -th cell indicates the number of times the actual i -th anomaly location was predicted as the j -th anomaly location, presented as a ratio with respect to the total number of actual inspection test cases. Correct “localizations” appear along the diagonal, while incorrect ones are in the off-diagonal elements. The rightmost column indicates the percentages of correctly (in green) and incorrectly (in red) localized test cases with respect to the total inspection test cases for each location. Conversely, the last row showcases the percentages of correctly (in green) and incorrectly (in red) localized test cases relative to the total test cases (80 of each location). Lastly, the lowest and rightmost cell specifies the overall correct localization rate (in green) and false localization rate (in red) across all four locations. Notably, as observed in the previously mentioned cell of the matrices, the MM-PSD method slightly overpowers the MM-AR, achieving an overall correct localization rate of 98.12% compared to the 96.57% achieved by the latter. The k-NN-PSD method performs well, with an overall correct localization rate of 93.67%. On the other hand the k-NN-AR method shows less effectiveness in localizing the propeller anomaly for this task, achieving a lower overall correct localization rate of 87.75%.

(a) MM-AR based method						
Estimated Class		F0001	F0010	F0100	F1000	
	F0001	76/80 23.75%	0/80 0%	0/80 0%	0/80 0%	100% 0%
	F0010	0/80 0%	74/80 23.12%	0/80 0%	1/80 0.31%	98.6% 1.4%
	F0100	0/80 0%	0/80 0%	80/80 25%	0/80 0%	100% 0%
	F1000	4/80 1.25%	6/80 1.75%	0/80 0%	79/80 24.7%	88.7% 1.3%
	95% 5%	92.5% 7.5%	100% 0%	98.8% 1.2%	96.57% 3.43%	
(b) MM-PSD based method						
Estimated Class		F0001	F0010	F0100	F1000	
	F0001	74/80 23.12%	0/80 0%	0/80 0%	0/80 0%	100% 0%
	F0010	0/80 0%	80/80 25%	0/80 0%	0/80 0%	100% 0%
	F0100	0/80 0%	0/80 0%	80/80 25%	0/80 0%	100% 0%
	F1000	6/80 1.75%	0/80 0%	0/80 0%	80/80 25%	93% 7%
	92.5% 7.5%	100% 0%	100% 0%	100% 0%	98.12% 1.88%	
(c) k-NN-AR based method						
Estimated Class		F0001	F0010	F0100	F1000	
	F0001	76/80 23.75%	0/80 0%	0/80 0%	0/80 0%	100% 0%
	F0010	0/80 0%	61/80 19%	0/80 0%	15/80 4.6%	80.3% 19.7%
	F0100	0/80 0%	0/80 0%	80/80 25%	0/80 0%	100% 0%
	F1000	4/80 1.25%	19/80 5.9%	0/80 0%	65/80 20.3%	73.9% 26.1%
	95% 5%	76.2% 23.8%	100% 0%	81.2% 18.8%	87.75% 3.43%	
(d) k-NN-PSD based method						
Estimated Class		F0001	F0010	F0100	F1000	
	F0001	74/80 23.12%	0/80 0%	0/80 0%	0/80 0%	100% 0%
	F0010	0/80 0%	76/80 23.75%	0/80 0%	10/80 3.22%	88.4% 11.6%
	F0100	6/80 1.9%	0/80 0%	80/80 25%	0/80 0%	93% 7%
	F1000	0/80 0%	4/80 1.21%	0/80 0%	70/80 21.8%	94.6% 26.1%
	92.5% 7.5%	95% 5%	100% 0%	87.5% 12.5%	93.67% 6.33%	
		True Class				

Figure 7 – UAV propeller anomaly localization results via confusion matrices: (a) the MM-AR based method, (b) the MM-PSD based method, (c) the k-NN-AR based method and (d) the k-NN-PSD based method (correct localizations indicated by green – mislocalizations by red; 320 inspection test cases).

6. Discussion

The results achieved by the MM based methods demonstrate their efficacy in vibration-based detection and localization of early-stage UAV propeller anomalies. The unsupervised MM based methods achieved high anomaly detection rates under unknown operating uncertainty using a minimal number of vibration signals for their training and a single sensor, with the U-MM-PSD method, in particular,

reaching higher true positive rates and minimal false alarms compared to the U-MM-AR for all propeller anomalies. The supervised versions of the above methods witnessed similar performance in localizing the early-stage UAV propeller anomalies, with the MM-PSD method reaching the highest correct localization score. It should be noted that the performance of the typical OCSVM and k-NN methods has been very good, yet inferior to the MM based ones, revealing thus the superiority of the latter over typical machine learning models for anomaly detection and localization. The good performance of the OCSVM and k-NN methods may be attributed to the fact that their training has been based on dynamics-informed features, such as the Welch PSD estimates and AR model parameter vector.

The above methods may lead to real-time, accurate health monitoring for a single UAV, while with proper training, their application may be extended to multiple UAVs that operate in collaborative environments, providing shared situational awareness among all UAVs in the fleet. The above methods are automated and executed on-line, allowing UAVs within a collaborative fleet to autonomously assess their operational status and communicate this information across the system. This autonomous communication is crucial for maintaining fleet integrity and operational continuity, especially in complex flight formations or coordinated tasks where the failure of a single UAV could compromise the entire operation.

7. Concluding remarks

In this study, the vibration-based detection and localization of UAV propellers with early-stage anomalies with no obvious effects on the in-flight vibration signal characteristics under unknown uncertainty have been investigated and addressed. In particular, two machine learning methods within a Multiple Model framework that rely on data-driven stochastic non-parametric and parametric models, estimated from vibration signals of a single sensor, for the UAV dynamics representation have been employed. The anomaly detection sub-problem, has been tackled via two unsupervised methods, the U-MM-PSD and U-MM-AR, that employ the Welch-based Power Spectral Density estimates and AutoRegressive parameter vectors as sensitive to propeller anomaly features, respectively. On the other hand, the UAV propeller anomaly localization sub-problem has been achieved via their supervised counterparts, MM-PSD and MM-AR, which rely on the aforementioned respective features. Based on all the above, as well as the pertinent state-of-the-art, the main concluding remarks of the study are:

- (i) A key advantage of the postulated MM based methods is that UAV propeller anomaly detection and localization are achieved using dynamics-informed features, the Welch based PSD estimates and the AR parameter vectors, which unlike the static, scalar, quantities, exploit maximum information of the UAV dynamics enhancing thus their sensitivity to UAV propeller anomalies. Another advantage of the postulated methods is that their training requires a limited number of in-flight acceleration signals using only a single sensor, while a minimal number of hyperparameters (Welch window length, AR model order selection and MM dimensionality) needs to be determined, thus pinpointing their simplicity.
- (ii) The U-MM-PSD method achieves almost excellent performance in detection of the considered propeller anomalies, achieving a correct detection rate of 100% for F0001, F0100, F1000 and 87.75% for the F0010 anomalies scenarios, outperforming the U-MM-AR method which also reaches 100% correct detection for F0001, F0100, and F0010, but lagging behind with a correct detection rate of 57% for the F1000 propeller anomaly. The comparison with the OCSVM variants has indicated that the performance of the OCSVM-PSD is very good, reaching 100% correct detection rate for propeller anomalies F0001, F0100 and F1000, yet failing completely to detect F0010. On the other hand, the OCSVM-AR variant shows significantly inferior performance, reaching the highest correct detection rate 78% for F0010.
- (iii) Similarly, the MM-PSD method slightly surpasses the MM-AR, achieving an overall correct localization rate of 98.12% compared to 96.57%. The comparison with the k-NN variants indicated that both k-NN-PSD and k-NN-AR are performing well yet still lagging behind, achieving an overall correct localization rate of 93.67% and 87.75%, respectively.

- (iv) A more general remark is that the employed MM methods may offer valuable information about the overall UAV state under unknown operating conditions and uncertainty. In addition, their simplicity renders them a highly promising option for real-time applications concerning UAVs that may also constitute part of a broader UAV Condition Based Maintenance strategy.

Acknowledgements

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