Machine-learning Framework for Online Probabilistic Rotor Fault Detection, Identification, and Quantification on a Multicopter using Boom Strain Signals

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ABSTRACT

A robust machine-learning (ML) based framework for online rotor fault detection, identification and quantification in multicopters while effectively rejecting the effects of gusts is introduced. The framework employs in-flight time-series data obtained from the a 2 kg gross weight hexacopter flying at a forward speed of 5 m/s. A concise overview of the rational selection of signals from the on-board sensors network, and using those signal properties for training the ML algorithms are presented. This scheme relies on static properties of the local signals, the strain gauge readings at each boom, to distinguish between gust affected healthy aircraft and different rotor fault types. A simple neural network with input as the statistical mean of the above signals can perform simultaneous online rotor fault detection and identification with exceptional decision-making speed and accuracy of fault classification. Next, a simple linear regression predicts the rotor degradation value with 95% confidence intervals from the strain at the boom on which the faulty rotor is mounted. Indicative results at a few test operating conditions (not used in the training phase) demonstrate the generalization capability of the method. It can detect and identify a rotor fault of even 10% degradation while distinguishing it from an aggressive gust of 10 m/s magnitude. The average time of fault detection is less than 0.3 s with classification and quantification accuracy over 97% and 95%, respectively.

INTRODUCTION

Urban air mobility (UAM), enabled by autonomous electric VTOL (eVTOL) aircraft is set to revolutionize urban transport. A NASA sponsored study concluded UAM is a viable option and assessed its available market value at $500B (Ref. [1]). But, the operational success of on-demand aviation service for mass transportation requires absolute safety and reliability. The preliminary safety target of UAM utilizing the airspace over dense urban environments has been established to be twice as safe as driving by Uber Elevate (Ref.[2]), with the expected improvement toward airline aviation levels of safety through innovation with full autonomy and large amounts of data from real-world operations after the first generation VTOL aircraft are in production. Therefore, the current interest is towards real-time system-level awareness and safety assurance in UAM aircraft utilizing in-flight data streams. The goal of this line of work is the development of a data-driven and probabilistic rotor fault diagnosis framework in multicopters which will provide online information about rotor faults, critical for control reallocation or vehicle reconfiguration to complete the flight safely.

Multicopters have been identified as a potential platform for future UAM aircraft development due to their rotor redundancy, design flexibility, ability to integrate distributed electric propulsion, and their superior fault robustness and compensation capabilities. These are complex systems that exhibit strong non-linear dynamic coupling between rotors, structural components, fuselage, and control inputs, as well as time-varying and cyclo-stationary behavior and pose significant system modeling and identification challenges when compared to fixed-wing aircraft. These issues, as well as potential solutions, have been explored in the literature.

There are three main types of rotorcraft faults, classified by their location, namely actuator, sensor, and component faults, which have been addressed by various model representations (linear time-invariant, linear parameter varying, non-linear, and multibody dynamics models and Kalman Filters) (Refs. [3–8]). signal processing techniques (in time- and frequency-domain, Kalman filter) (Refs. [9–14]), as well as computational intelligence approaches (neural networks, fuzzy logic, hidden Markov models, dynamic Bayesian network, and Gaussian mix-
ture models, support vector machines) (Refs. [15]–[24]) for a detailed review the interested reader is referred to (Ref. [25]). However, the available studies are either limited by analytical model building with the assumption of physical knowledge of the system available or mostly concentrate on structural faults of blades, propellers, powertrain, etc. in rotorcraft.

Hence, the problem of multicopter rotor fault diagnosis under operating and environmental uncertainty was approached with statistical time series methods. These methods have been used extensively in structural health monitoring (Refs. [26]–[29]) and detection of various types of faults in fixed-wing aircraft systems (Refs. [30]–[31]), due to their simplicity, efficient handling of uncertainties, no requirement of physics-based models, and applicability to different operating conditions. Zhao et al. have validated a stochastic hybrid system for health evaluation in multicopters under simulated sensor anomalies (Ref. [32]).

Previously, Dutta et al. achieved fast and accurate online rotor failure detection and identification via a novel application of stochastic time-series models and proper statistical decision-making under pre-determined confidence levels to a hexacopter flying forward under different turbulence levels and uncertainty as well as varying forward velocity and gross weight in Refs. [33]–[34].

Another class of stochastic methods is the machine learning (ML) techniques adept in clustering, classifying, and extracting useful features from high-dimensional, noisy data. Neural networks (NN) (Refs. [15]–[17]) and support vector machines (Refs. [23]–[24]) are being widely used in FDI to make a decision on the current state of a dynamic system. Ganguli et al. (Ref. [16]) and Morel et al. (Ref. [15]) employed NNs to detect and trace faults and defects of helicopter rotor blades using noise-contaminated vibration data. Multicopter rotor structural damage detection and identification and has been demonstrated by Iannace et al. in Ref. [17] with acoustic signals and NNs, and by Bondrya et al. in Ref. [24] via support vector machines based on measurements of acceleration from the onboard IMU (Inertial Measurement Unit). To address the issues of focus on data-fitting and black-box modeling with ML algorithms, Dutta et al. proposed an innovative time-series assisted neural network for online rotor FDI. The features, acting as the input layer of the NN, were extracted from a statistical time-series model of the healthy aircraft for improved physical explainability of the data-driven scheme. Its excellent FDI performance with respect to accuracy and computation time was demonstrated in Ref. [35].

To the authors’ best of knowledge, papers pertaining to actuator fault quantification is scarce. Fault magnitude information obtained online can facilitate switching over to a more optimal control scheme and planning alternative trajectories with limited control authority depending on the fault severity. Therefore, to fill this research gap the previously developed time-series assisted neural network was extended to determine three discrete fault levels (mild, caution, and urgent) in addition to rotor fault detection and classification while differentiating them from random gusts in Ref. [36]. To enable continuous fault quantification, a unified statistical time-series framework was developed based on Functionally Pooled (FP) models, that are capable of representing an aircraft dynamics under rotor faults for a continuum of fault magnitudes of a particular rotor fault type (Ref. [37]). This framework was applied to a flexible-boom hexacopter, using remote signals from the Inertial Measurement Unit (IMU), and local signals from sensors placed on individual booms. Besides accurate fault detection and identification by either type of signals, improvement in continuous rotor fault quantification was observed for local signals over remote signals.

The objective of this paper is to develop a simple data-driven framework for online rotor fault detection, identification, and quantification in multicopters flying forward under atmospheric turbulence, wind gusts, and uncertainty. A novel application of ML algorithms in the context of probabilistic fault diagnosis on a hexacopter using suitable sensor data (time-series signals) is presented. Its performance with respect to prompt detection, accurate identification, gust distinction capability, and precise quantification under turbulence, random gusts, and rotor faults is investigated.

**HEXACOPTER MODEL AND DATA GENERATION**

**Physics-Based Modeling of Multicopter System**

A flight simulation model has been developed for a regular hexacopter (Fig. 1) using summation of forces and moments to calculate aircraft accelerations. This model is used as the source of simulated data under varying operating and environmental conditions, as well as different fault types. Rotor loads are calculated using Blade Element Theory coupled with a $3 \times 4$ Peters-He finite state dynamic wake model (Ref. [35]). This model allows for the simulation of abrupt rotor failure by ignoring the failed rotor inflow states and setting the output rotor forces and moments to zero.

A feedback controller is implemented on the nonlinear model to stabilize the aircraft altitude and attitudes, as well as track desired trajectories written in terms of the aircraft velocities. This controller is designed at multiple trim points, with gain scheduling between these points to improve performance throughout the flight envelope. The control architecture is detailed in Ref. [39]. This control design has been demonstrated to perform well even in the
Figure 1: Schematic representation of a regular hexacopter event of rotor 1, 2 or 6 failure, with no adaptation in the control laws themselves.

The 12 rigid body states are defined in Eq. (1):

\[ \mathbf{x} = \{X, Y, Z, \phi, \theta, \psi, u, v, w, p, q, r\}^T \]  

(1)

The input vector is comprised of the first four independent multirotor controls for collective, roll, pitch and yaw and is defined in Eq. (2):

\[ \mathbf{u} = \{\Omega_0, \Omega_R, \Omega_P, \Omega_Y\}^T \]  

(2)

The booms of the hexacopter are modeled as one-dimensional, Euler-Bernoulli beams, with an added tip mass and loading, and are coupled to the rigid body motion of the vehicle. The positive bending deflections in the in-plane and out-of-plane of the hub are illustrated in Fig. 2. Torsion is neglected. The beam equations are discretized in space using the Ritz method with 2 modes in direction, as given in Eq. (3), with polynomial shape functions, \( \phi \) that satisfy the geometric boundary conditions given by Eq. (4). To facilitate the inversion of the mass matrix that arises from this discretization, these polynomials are chosen to be orthogonal. The modes are obtained via eigen-analysis of the beam in a vacuum.

\[ v = \sum_{i=1}^{2} \eta_{v_i} (t) \phi_{v_i}(l) \]  

(3)

\[ w = \sum_{i=1}^{2} \eta_{w_i} (t) \phi_{w_i}(l) \]  

(4)

where, \( \eta \) represents the modal deformations. \( l \) is the non-dimensional boom coordinate, representing the distance of a point on the boom from its root normalized by the boom length. It ranges from 0 to 1, denoting the boom root and boom tip, respectively. The geometric boundary conditions are given by:

\[ w(0) = w'(0) = 0 \]  

\[ v(0) = v'(0) = 0 \]  

(5)

In the above equations, ‘‘ and ‘‘ imply \( \frac{d}{dl} \) and \( \frac{d}{dt} \), respectively.

The sensor signals can be calculated using the above aircraft states obtained from the flight simulation (See Appendix A).

Incorporation of Turbulence

A continuous Dryden wind turbulence model (Ref. 40) has been incorporated in the flight simulation model to replicate realistic flight conditions. The Dryden model is dependent on altitude, length scale, direction-cosine matrix, body velocity, and turbulence intensity. It outputs the linear and angular velocity components of continuous turbulence as spatially varying stochastic signals. These signals are added to the inflow of each of the rotors by transforming them from the aircraft center-of-gravity to the corresponding rotor locations, to account for the effect of the turbulent wind velocities on the multicopter. The proper combination of the turbulence block parameters determines the fit of the signals to observed turbulence (Ref. 41). In this system, the altitude is taken as 5 m, and the length scale as the hub-to-hub distance of the hexacopter which is 0.6096 m (2 ft). The direction-cosine-matrix and forward velocity are determined from the instantaneous aircraft states during the simulation.

Introduction of Gusts

Next, similar data sets under different magnitude (3-10 m/s) and directions of gusts for healthy flight under severe levels of turbulence have been generated (Ref. 42). The gusts follow a ‘1-cosine’ shape with gradual increase, followed by a steady-state and gradual decrease
Table 1: Dataset summary

<table>
<thead>
<tr>
<th>Aircraft state</th>
<th>Number of Datasets</th>
<th>Signal Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy Turbulence Levels</td>
<td>1+1*</td>
<td>60 s</td>
</tr>
<tr>
<td>Severe</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Light</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Gasts</td>
<td>Gust Wind Speed (m/s)</td>
<td>20 s</td>
</tr>
<tr>
<td>8.67</td>
<td>3.46</td>
<td>5, 10</td>
</tr>
<tr>
<td>8+8</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td>Rotor Faults</td>
<td>Degradation (%)</td>
<td>60 s</td>
</tr>
<tr>
<td>1, 2, 6</td>
<td>10,30,90</td>
<td>20,40,100</td>
</tr>
</tbody>
</table>

Sampling frequency: \( F_s = 10 \text{ Hz} \)

* indicates training data (Ref. [33], as shown in Fig. 3a). In the simulations, the gusts commence at 4 s with a gradual increase from 0 to its full magnitude in the next 2 s, after which it becomes steady and lasts for 10 s, before gradual decrease to zero again in the next 2 s. Therefore, in the simulated data gusts last from 4-18 s in a span of 20 s of healthy flight. In real flight, the magnitude, direction, time and duration of gusts can be random in nature depending upon the region, altitude, and weather conditions. The magnitude and direction of the gusts considered in this study has been given in Appendix B, Table 6. The wind velocity directions are denoted by unit vectors with the positive X, Y, Z directions shown in Fig. 3b.

**Data Generation**

The data sets are generated through a series of simulations for different fault types and magnitude under severe of turbulence for the aircraft flying at 5 m/s and having a gross weight of 2 kg. Note that the rotor failures addressed in this paper are: front rotor (rotor 1) and the right-side rotor (rotor 2), and left-side rotor (rotor 6) faults (See Fig. 1). Rotor degradation has been replicated by reducing the commanded speed of that particular rotor by a multiplier ranging from 0 to 1, with ‘0’ denoting 0% rotor degradation, i.e., healthy aircraft and ‘1’ implies 100% rotor degradation or complete rotor failure.

**METHODOLOGY**

**Influence of Gusts on previously developed Statistical Time-series framework for Rotor Fault Diagnosis**

In a previous study, a sensor signals based statistical time series method that is capable of effective fault detection, identification, and magnitude estimation within a unified framework for a hexacopter flying under turbulence and uncertainty is presented (Ref. [37]). The method is based on the functionally pooled (FP) models (whose parameters are functions of some operating conditions) and proper statistical decision-making schemes. FP models are capable of accurately representing the aircraft dynamics under rotor faults for a continuum of fault magnitudes of a particular rotor fault type. These models for different rotor faults on a multicopter can be identified from available time-series sensor data in the baseline phase. In its inspection phase, there are three distinct steps taking place within a probabilistic framework: step I involves fault detection, step II involves fault identification after fault compensation by the controller, and step III involves precise fault quantification within the identified type of fault. Fault magnitude is continuous, involving an infinite number of potential fault magnitudes ranging from healthy to complete failure. The validity and effectiveness of the method have been assessed via a proof-of-concept application to rotor fault diagnosis with remote and local signals, i.e., z-acceleration signals from the system Inertial Measurement Unit (IMU) and the z-accelerations at the respective boom-tips, respectively. It has been demonstrated that effective fault detection, fault mode identification, and fault magnitude estimation with uncertainty bounds is possible even for “unmodeled” (not used in training) rotor degradation with very limited number of sensor signals (even with a single response signal from the IMU) through powerful signal analysis techniques. An important observation was that fault quantification performance, i.e., the accuracy of fault estimation and tighter uncertainty bounds, was improved via the use of local sensors (boom accelerations) compared to remote sensors (body acceleration).

However, when gusts are introduced in healthy flight, the above method falsely detects the response of the healthy aircraft to gusts as rotor faults, with both the remote and the local signals. To account for random gusts the method needs to be significantly extended, such as identifying a number of time-varying models with the non-stationary signals under gusts of different wind velocity and direction. Moreover, since these methods involve identification of dynamic models from signals, the signals need to be sampled at relatively higher rate after proper filtering to capture the aircraft dynamics and flexible boom natural frequencies.

The current work aims to address the issue of gusts in a simpler fashion, than needed by statistical decision-making with properly identified stochastic models. Previously, the problem of distinguishing gusts from rotor faults had been tackled by using the correlation between aircraft control and response signals in a rigid boom hexacopter, via a systematic analysis detailed in Ref. (Ref. [36]). Currently, with the consideration of boom flexibility, local signals contain information about the actual rotor speeds, which can be utilized for rotor fault
diagnosis while rejecting gusts. Also, static modeling
signals will be attempted to forego the need for higher
sampling rate to capture the structural dynamics of the
booms.

Selection of Signals

Flight simulation for the hexacopter was performed at
operating conditions specified in Table 1. Figures 5a
through 7b show time histories of strain gauges placed
at the boom roots (where the boom connects to the hub)
for cases of healthy flight with and without gusts, and
different rotor fault scenarios. The x-axis shows the time
in seconds, as the y-axis gives the value of out-of-plane
(perpendicular to the rotor hub plane) strain at each of
the 6 booms. These local signals, sampled at 10 Hz, will
be utilized for the development of the machine-learning
based framework of probabilistic fault detection, identifi-
cation and quantification for their certain characteristics,
as discussed in the following paragraphs.

Figure 5a show the strain at each of the boom root in the
out-of-plane directions while flying at 5 m/s with gross
weight 2 kg under severe turbulence in healthy condition.
Though, the signals are stochastic in nature, they pos-
sess definite statistical mean value for each of the boom.
These mean values of strain on each boom depend on the
corresponding the rotor thrust and hence the rotor speeds.
Thus, these signals give an insight into the commanded
rotor speeds, when there are no rotor faults in the system.

Figures 5b and 6a show the time history of the strain sig-
als under two indicative gusts considered in this study.
The gusts commence at 4s and last until 18 s, shown by
the black dashed vertical lines. There are no rotor faults
in the system. In Fig. 5b, the gusts are coming from
all the directions, and result in significant change in the
mean values of strain signals, mostly during the steady
gust phase lasting from 6 s to 16 s. It can be observed
that the absolute value of strains in booms 4 and 6 de-
creases during gust, mimicking a rotor fault, where the
rotor loses thrust. The aim of this study is to prevent such
situations being misclassified as rotor faults by consid-
ering the response of all the rotors, as reflected in their
corresponding strain values. Figure 6a shows a gust 10
m/s coming directly from the direction of flight, which ef-
ectively increases the flight speed. This is countered by
the controller decreasing the nose-down pitch to maintain
flight at the commanded speed of 5 m/s, by increasing
the speed of rotor 1 and decreasing that of rotor 6, indicated
by the change in mean value of strain.

Figures 6b to 7b shown the strain signals under the con-
sidered rotor faults and their varying magnitudes. For
the simulation results presented, the rotor faults occurs at
t = 10 s, as indicated by the vertical black dashed line. It
should be noted that due to faults, the signals have a tran-
sient response before reaching controller-compensated
steady state. In Fig 6b, 30 % degradation of rotor 1 has
resulted in the decrease of absolute value of strain on
boom 1 due to loss of thrust. To compensate for this fault,
rotor 4 also slows down. Similarily, in Figs 7a and 7b the
response of other rotors to rotor 2 and 6 faults, respec-
tively can be observed.

The pattern of how the rotors respond to gusts and faults
will be utilized to distinguish them. Also, note that con-
trary to faults, the change in signals due to gusts last only
for its duration. Rotor faults cannot be reversed and hence
the change in the signals continue through the entire flight
time.

Finally, it can be observed that the rotor fault magnitude
has a direct relation with the value of strain on the boom it
is mounted upon, as shown in Fig 8. Under complete fail-
Figure 5: Time history of out-of-plane strain at each of the booms root under (a) healthy flight (b) healthy flight with gusts, $8.67(-0.57\hat{i} + 0.57\hat{j} + 0.57\hat{k})$ m/s

Figure 6: Time history of out-of-plane strain at each of the booms root under (a) healthy flight with gusts, $10(-1\hat{i} + 0\hat{j} + 0\hat{k})$ m/s (b) 30% degradation of rotor 1

ure of rotors or 100% degradation, the strain value goes to zero, due to zero thrust generated. The variation of strain on the respective boom can be employed to estimate the fault magnitude, after it is detected and identified.

Development of the Machine-Learning Framework

In this section, the development of a data-driven framework for probabilistic rotor fault diagnosis utilizing the carefully selected in-flight data streams via the application of common ML algorithms is presented. It has been
observed from the 6 local signals (out-of-plane strain at all boom roots) that the change in their absolute magnitude closely reflects the actual rotor speeds. Under different operating conditions, such as healthy flight with or without gusts, and different rotor fault scenarios, the statistical mean of signals will change relative to each other, forming some distinguishing patterns. These patterns can be classified via a pattern recognition algorithm, such as a single hidden layer neural Network to simultaneously detect and identify faults. If and when a fault is detected, the signal from the faulty rotor boom will be used for fault quantification by a simple linear regression framework. The workflow of the proposed rotor FDI technique is given in Fig. 9.

**Neural Network** Neural networks (NN), inspired from biological learning systems form a distributed information processing system consisting of neurons arranged in layers and executed in parallel. The neurons are non-linear information processing elements and the interconnections between these neurons network are known as weights. These weights are learned through supervised training algorithms, where the training data contain the inputs and their corresponding output labels. NNs can compactly represent information, perform excellent classification, and can accommodate noise and uncertainty in data with carefully chosen features and regularization parameters. These characteristics make it attractive for the present application, where the aim is to develop a robust rotor FDI framework with signals affected by atmospheric disturbances encountered in actual flight.

From previous section, it has been observed that the values of out-of-plane strains at each boom root relative to each other can be a useful feature for a pattern recognition algorithm to determine the aircraft health status. To this end, a single-hidden layer is trained to output one of the 4 classes: healthy aircraft, rotor 1 fault, rotor 2 fault, rotor 3 fault.
and rotor 6 fault with the mean value of the 6 strain signals over some time window as input. The input layer is denoted by $x^T$ and the output layer is denoted by $h(x)$ and is related by the following equation:

$$h(x) = \sigma \left( W_2^T \left( \theta \left( W_1^T x + B_1 \right) \right) + B_2 \right)$$  \hspace{1cm} (6)$$

where, $\theta(s)$ indicates the hyperbolic tangent activation function, and $\sigma(z)$ indicates the softmax activation function. The weight matrices and bias vectors for the two layers denoted by $W_1, W_2$ and $B_1, B_2$ are determined in the baseline training phase by backpropagation learning techniques to minimize classification error. Using the cross-entropy error as cost function and softmax function in the output layer, the probabilities of each input element belonging to a output class can be obtained (Ref. 44).

The first class consists of healthy signals under severe turbulence with and without gusts (8.67 m/s with different directions). The rotor 1, 2, and 6 fault classes have been trained with the respective rotor fault signals under 10, 30, 50, 70, and 90% degradation (denoted as training data in Table 1). Note that the training data sets are divided into disjoint windows of 1 s. Each data-point consists of the mean of the 6 strain signals that are calculated over a single window and its corresponding true class label. The number of data-points should be balanced for the different classes to avoid classifier bias. The details of this NN are given in Table 2.

### Table 2: Details of the neural network training

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Type</td>
<td>Mean of the out-of-plane strain at all boom roots</td>
</tr>
<tr>
<td>Input Layer Size</td>
<td>6</td>
</tr>
<tr>
<td>Training Function</td>
<td>Scaled Conjugate Gradient</td>
</tr>
<tr>
<td>Hidden Layer Size</td>
<td>3</td>
</tr>
<tr>
<td>Output Classes</td>
<td>4 (Healthy and 4 (Rotor 1,2 &amp; 6 faults)</td>
</tr>
<tr>
<td>Cost Function</td>
<td>Cross-Entropy</td>
</tr>
<tr>
<td>Activation Function</td>
<td>1st layer - Hyperbolic Tangent Function, 2nd Layer - Softmax</td>
</tr>
<tr>
<td>Data Partition</td>
<td>Learning: Validation: Test = 50:25:25 % of Training Data</td>
</tr>
<tr>
<td>Performance</td>
<td>$2.7 \times 10^{-7}$</td>
</tr>
</tbody>
</table>

The linear regression model is fitted (MATLAB function: *fitlm*) as follows:

$$y = x \beta + \epsilon \quad x = [1 \ x] \quad \beta = [\beta_1 \ \beta_2]^T$$  \hspace{1cm} (7)$$

where ‘$y$’ denotes the rotor degradation value, ‘$x$’ mean strain at faulty rotor boom and ‘$\beta$’ the vector of coefficients to be learnt from the training data.

The linear regression model is trained with the faulty training data denoted in Table 1. For rotor 1 faults, only the mean strain (calculated over window of 1 s) on boom 1 is used, with the labels being the true rotor degradation values. Similarly, for rotor 2 and 6 faults, the strain signals from boom 2 and 6 are used for training, respectively. The model outputs the predicted rotor fault magnitude, once the fault is identified by the NN along with the 95% confidence intervals according to Scheffé’s method.

The details of the trained linear regression model is given in Table 3.

### RESULTS AND DISCUSSION

Current in-flight data streams have been used for online monitoring of aircraft health conditions. A window of 1
Table 3: Details of the linear regression training

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inputs</td>
<td>Mean of the out-of-plane strain at faulty rotor boom &amp; rotor degradation value</td>
</tr>
<tr>
<td>Number of coefficients</td>
<td>2</td>
</tr>
<tr>
<td>$R^2$ fit</td>
<td>0.97</td>
</tr>
<tr>
<td>RMSE</td>
<td>4.9% rotor degradation</td>
</tr>
<tr>
<td>Output</td>
<td>Rotor degradation with confidence intervals</td>
</tr>
</tbody>
</table>

$s$ of each of the 6 signals have been processed through workflow depicted in Fig. 10. To ensure a continuous decision making, the window is updated every 0.1 s. The computation time required to make a decision is less than 0.01 s, which is less than the window update time, making it suitable for real-time monitoring. A fault is detected when the neural network outputs any class other than healthy, and that output class determines which of rotor 1, 2, or 6 has failed, enabling simultaneous fault detection and identification. Note that this decision is attached with a probability estimate which can help the operator to have a better insight of the fringe cases such as confusion between very mild degradation and strong gusts where the probability estimates of the two confusing classes will be about 50%, whereas in normal cases the confidence of a decision is generally more than 95%. After fault detection and identification, the linear regression model predicts the fault magnitude and its 95% confidence intervals using the strain from the boom on which the faulty rotor is mounted.

Indicative Results for Online Health Monitoring

Few indicative results for online monitoring of aircraft health with the current decision-making framework has been presented in Figs. 11a through 13b. The top subplots shown the mean of signals over a window of 1 s, updated every 0.1 s, that are used as input to the decision-making framework. The bottom subplots show the decision output by the framework, at each time window. The x-axis shows the time of flight in seconds in both the plots. Note that the online monitoring starts at 1 s to collect signals for the required time window. If the decision marker is shown in +, the aircraft is healthy. Otherwise, the markers *, o, and x denote fault of rotor 1, 2, and 6 respectively. The fault magnitude is shown by the y-axis in the bottom plots.

Figure 11a shows the correct health prediction for a healthy flight under light turbulence (a condition not used during training phase). Figures 11b and 12a demonstrates that even under aggressive gusts of magnitude 8.67 m/s and 10 m/s, respectively which may cause significant change in the aircraft dynamics, the trained NN based on the static properties of the local signals correctly classifies it as a healthy aircraft.

Figures 12b to 13b show indicative results for online monitoring under rotor faults. Note that the rotor fault magnitudes (20, 60 and 80% degradation) considered were not used in the training phase. In the top plots the time of fault commencement is shown in black vertical dashed lines. In the bottom plots the time of fault detection is shown in brown vertical dashed lines. A fault is always detected within 0.6 s of its commencement with longer time needed for mild degradation levels. In the bottom plots the true value of rotor degradation is shown by a grey horizontal line. It is observed that the true fault magnitude almost always lie within the 95% confidence intervals of the predicted values (shown by the vertical segments at each decision marker), denoting correct fault quantification. However, just after the fault detection and classification, depicted by the marker colour changing from green, the fault quantification becomes accurate only after the transient phase of the signals are over and they become steady (see Figs. 6b to 7b). The precision of fault quantification, i.e., the absolute difference between the predicted and true value is mostly less than 5% of rotor degradation in the steady state. The average range of 95% confidence intervals is 20 % rotor degradation.

Figure 10: Flowchart for online monitoring of rotor faults
Summary Results for the Performance

To ascertain the generalization capability of the neural network, data from various unknown operating conditions which have not been used to train it, have also been used in the inspection phase. These conditions include moderate and light levels of turbulence in healthy flight, gusts of 5 m/s, 10 m/s and 3.46 m/s, and rotor faults of 20, 40, 60, 80, and 100% degradation (See Table 1). The performance of this framework on test data is summarized in Table 4. For each dataset, a number of decisions are made throughout the flight time with moving windows. The fault classification and quantification accuracy denotes the percentage of those decisions where the correct health condition is determined, and the if the true rotor degradation value lies in between the predicted 95% confidence intervals, respectively. The fault prediction error gives the average of the absolute error in fault magnitude estimation, and it is expressed in rotor degradation %.

It is observed that though the NN was trained with healthy data obtained under severe turbulence only, it gives perfect classification with healthy data under moderate and light turbulence levels too. For gusts with higher magnitude of wind velocity than used for training, the classification accuracy falls to 97.9%, otherwise it is very accurate. The rotor faults of 10% or more degradation, have been classified accurately. The fault quantification accuracy is about 98%. This is due to the transient signals, where the fault magnitude is predicted lesser than the value obtained with steady signals. The absolute error i.e., the absolute difference between the predicted and true value of fault magnitude, averaged over all datasets and decision points is 4.2% rotor degradation. The average time to detect a fault is less than 0.3 s. Mild rotor faults require more time to be detected, and faults over 50% degradation generally requires 0.1 s.

Comparison of the Unified Statistical Time-series Framework and the developed Machine-Learning framework

The machine-learning (ML) framework developed in this study has significant advantages over the previously established unified statistical time-series method. The most important is that the method developed in this study can distinguish aircraft response to gusts from that due to rotor faults, without any considerable extension of the nominal framework. The fault detection and identification in the ML framework is instantaneous and simultaneous at the commencement of fault. Whereas in the statistical time-series method, the fault identification only takes place after it has been compensated by the controller,

Figure 11: Decision making in inspection phase under (a) healthy flight under light turbulence (b) healthy flight with gusts, $8.67(-0.57\hat{i} - 0.57\hat{j} + 0.57\hat{k})$ m/s
because the identified models on which the decision-making depends on are valid with stationary signals only. Moreover, the signals need to be properly filtered and sampled at a higher sampling frequency ($F_s = 3333$ Hz). This ensures that the signals capture the aircraft and boom structural dynamics, for proper model identification to enable FDI by statistical time-series method. Longer signal window and more computation time is required for multiple binary hypothesis tests in statistical time-series method. The developed ML framework on the other hand, achieved high accuracy using signals’ window of 1 s, with signals being sampled at only 10 Hz. However, in the ML framework, 6 signals are being collected and processed, for which special sensors needs to be mounted on each of the booms, whereas the statistical time-series method can work only with a single signal obtained from the aircraft IMU.

**CONCLUSION**

This paper introduces a machine-learning framework to detect, identify, and quantify rotor faults in a 2 kg gross weight hexacopter flying at 5 m/s under turbulence, and uncertainty while accurately rejecting disturbance due to gusts. In the baseline phase, commonly used ML algorithms such as a neural network and a linear regression...
model are trained on basis of static properties of the out-of-plane strain signals obtained from strain gauges placed at each of the booms’ root. In its inspection phase, there are two distinct steps taking place within a probabilistic framework: step I involves simultaneous rotor fault detection and identification and step II involves fault quantification within the identified type of fault. Fault magnitude is considered to be continuous, involving an infinite number of potential fault magnitudes ranging from healthy to complete failure. The effectiveness of the method have been assessed via application to a number of “unmodeled” aircraft health conditions. The method is well-suited for online health monitoring of multicopters as demonstrated by the speed of decision-making, excellent accuracy with regard to determining gusts from different rotor faults, and precise fault magnitude estimation with uncertainty bounds.

The main conclusions drawn from this study are summarized as follows:

- The study – including the proof-of-concept application – has demonstrated that effective fault detection, fault mode identification, and fault magnitude estimation are possible based on judiciously selected sensors and signal analysis for extracting the embedded information pertaining to the aircraft health condition.

- Robust rotor fault detection, identification, and quantification for a hexacopter in forward flight have been achieved in real-time under different levels of turbulence, random gusts and uncertainty.

- Fault magnitude estimation at the nominal (point estimation) level is adequate, and at the probabilistic level it is accurate with close uncertainty bounds.

- The ML framework is better suited for real-time monitoring of aircraft health than the nominal unified statistical framework without any significant augmentation, provided proper instrumentation to monitor the strain on individual booms is available.

- A number of issues can be addressed in future work, e.g., the treatment of simultaneous multiple rotor fault scenarios, operation under varying flight speed and gross weight, and large uncertainties.

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**APPENDIX**

A. Signals

The data used in this study are obtained from simulation rather than experiments and therefore the sensor signals need to be calculated from the available aircraft states.

Generally, Inertial Measurement Units (IMUs) are composed of a 3-axis accelerometer and a 3-axis gyroscope and outputs the body accelerations (x, y, and z acceleration) and the angular rates (roll, pitch, and yaw rates), which can be determined from 12 rigid body states are defined in Eq. 1 as follows:

\[
\begin{align*}
\text{Body accelerations} &= \begin{bmatrix} \ddot{u} & \ddot{v} & \ddot{w} \end{bmatrix}^T \\
\text{Angular rates}, \omega &= \begin{bmatrix} p & q & r \end{bmatrix}^T
\end{align*}
\]

(8)

Figure 14: Position of a boom with respect to the hub and its deformations

These signals are referred to as remote signals.

The sensors mounted on the different locations on the individual booms, such as strain gauges and accelerometers are referred to as the local signals. These can be computed from the individual booms modal deformation shapes and state functions (Eqs. 5 and 3) using the following expressions:

\[
\begin{align*}
\text{Total deformation}, q &= \begin{cases} 
\sum_{i=1}^{2} \phi_{wi}(l) \eta_{wi} & \text{Out-of-plane} \\
\sum_{i=1}^{2} \phi_{vi}(l) \eta_{vi} & \text{In-plane}
\end{cases} \\
\text{Strain}, \epsilon &= \begin{cases} 
\sum_{i=1}^{2} \phi_{w'i}(l) \eta_{w'i} \times a/2 & \text{Out-of-plane} \\
\sum_{i=1}^{2} \phi_{v'i}(l) \eta_{v'i} \times b/2 & \text{In-plane}
\end{cases}
\end{align*}
\]

(9)

where, \(a\) and \(b\) are the width and height of the cross-section of the boom, respectively. \(l\) is the distance from the boom root where the sensor has been placed, normalized by the boom length.

<table>
<thead>
<tr>
<th><strong>Table 5: Boom properties</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>Boom Length (L)</td>
</tr>
<tr>
<td>Material</td>
</tr>
<tr>
<td>Cross-section</td>
</tr>
<tr>
<td>Outer dimension</td>
</tr>
<tr>
<td>Inner dimension</td>
</tr>
<tr>
<td>Flexural Rigidity</td>
</tr>
</tbody>
</table>

The accelerometer readings on each of the boom can be calculated as:

\[
\text{Acceleration} = \dot{r} + \omega \times \dot{r} + \omega \times r + \omega \times \omega \times r
\]

(10)
where,

\[ r = \begin{bmatrix} -L \cos \zeta \\ L \sin \zeta \\ -d \end{bmatrix} + \begin{bmatrix} -\sum_{i=1}^{2} \phi_i(t) \eta_i \sin \zeta \\ -\sum_{i=1}^{2} \phi_i(t) \eta_i \cos \zeta \\ \sum_{i=1}^{2} \phi_i(t) \eta_i \end{bmatrix} \]

Here, \( \zeta \) is the azimuth angle of the boom (See Fig. 14). \( L \) is the length of the boom and \( d \) is the vertical position of the boom from the center-of-gravity of the aircraft. The boom properties are given in Table 5.

Note that these derivations are shown for a single time instant, \( t \). Repeating this computations for the entire range of time will generate the time-series sensor data.

B. Gusts

The gusts considered in this study, along with their magnitude and direction are tabulated below.

<table>
<thead>
<tr>
<th>Label</th>
<th>Magnitude (m/s)</th>
<th>Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.67</td>
<td>0.57\hat{i} + 0.57\hat{j} + 0.57\hat{k}</td>
</tr>
<tr>
<td>2</td>
<td>8.67</td>
<td>0.57\hat{i} + 0.57\hat{j} - 0.57\hat{k}</td>
</tr>
<tr>
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</tr>
<tr>
<td>4</td>
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<tr>
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<tr>
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<td>-0.57\hat{i} - 0.57\hat{j} - 0.57\hat{k}</td>
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<tr>
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<tr>
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<td>0\hat{i} + \hat{j} + \hat{k}</td>
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