Detection and Diagnosis of Flight Anomalies in Small Unmanned Aerial Systems

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University of San Diego®

Talk Outline

- Introduction
  - Problem Domain and Research Statement
- Anomaly Detection
  - Requirements for Deep Learning based Anomaly Detectors
  - Heuristic-based Detectors and Real-time Anomaly Detection with Real-world Drones
  - Adaptive Monitoring for Resource Optimization
- Anomaly Diagnosis
  - Diagnosis of Root-Cause of Anomalies
- Data Collection and Community Support

Introduction

Drones in Various Sectors

FORBES > LEADERSHIP > LEADERSHIP STRATEGY

How Drones Are Shaping The Future Of Ultrafast Delivery Across American Suburbs

Gary Drenik Contributor

Follow

0

May 31, 2023, 10:00am EDT

Delivery Drone ADOBESTOCK_446167872

AUGUST 20, 2019

Using drones in agriculture to spray fields with Rantizo

by João Antunes in Forestry & Agriculture

SHARE

At California Blazes, NASA Team Observes How Drones Fight Wildfire

A drone being used in wildfire response operations is seen flying at the Dixie fire in Northern California in August 2021. Software developed by the STEReO project for coordinating multiple parts of a fire response could be used on a tablet in the field, much like this pilot is using today's commercially available software.
Credits: National Park Service/Joe Suarez

FRENCH SKI RESORT TURNS TO THERMAL DRONES TO AID RESCUE WORKERS

Haye Kesteloo / October 13, 2020 / Drones For Good, France

Drone Helps Firefighters Rescue Two from River in Maine

See the dramatic rescue footage.

By ABC News
July 1, 2015, 4:08 PM

Drone helps rescue trapped rafters

Jon Fingas
Reporter
Updated Thu, Jul 2, 2015 · 2 min read

Drones in Various Sectors

As of 2023, the FAA has registered a total of **863,728** drones in the United States.
352,222 for commercial purposes,
and **506,635** for recreational purposes.

The global drone market size is projected to **grow from $22.5 billion in 2020 to over $42.8 billion by 2025**, at a compound annual growth rate **(CAGR) of 13.8%.**

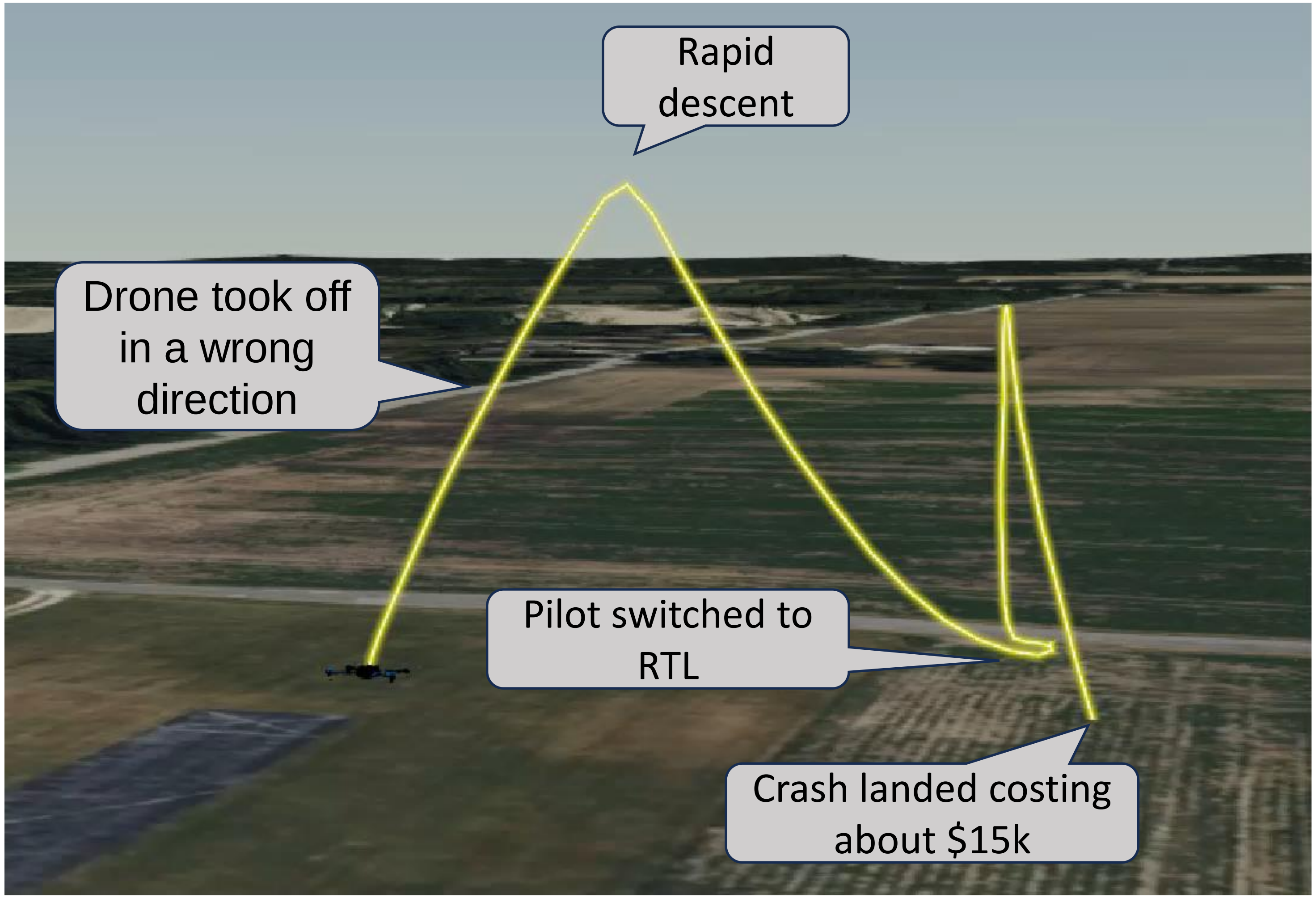
Commercial drone shipments expected to **rise by 66% from 2022 to 2024**, indicating robust industry demand and an expanding range of applications.

The Future

Research Statement

My research focuses on ***Real-time Detection and Diagnosis of Flight Anomalies*** *in small* Unmanned Aerial Systems (sUAS), commonly known as UAVs or Drones.

A Motivating Incident

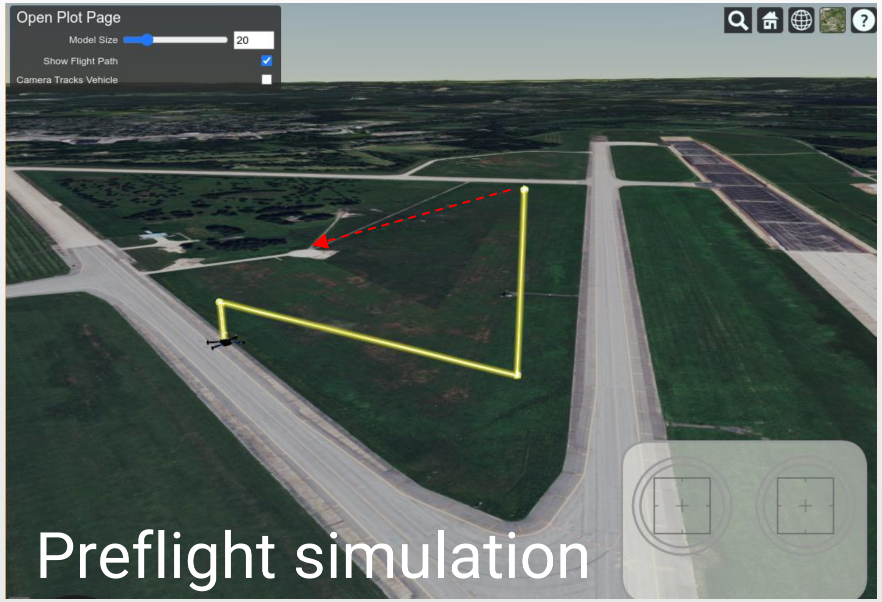


A post-accident photo of the UAV.

A test flight for checking computer vision capabilities of the UAV. It was supposed to take off, detect a person and then circle the person.

Another Incident

1



2

3

Post-mission, hovered for 20+ minutes for endurance test. Crashed in final minutes of flight!

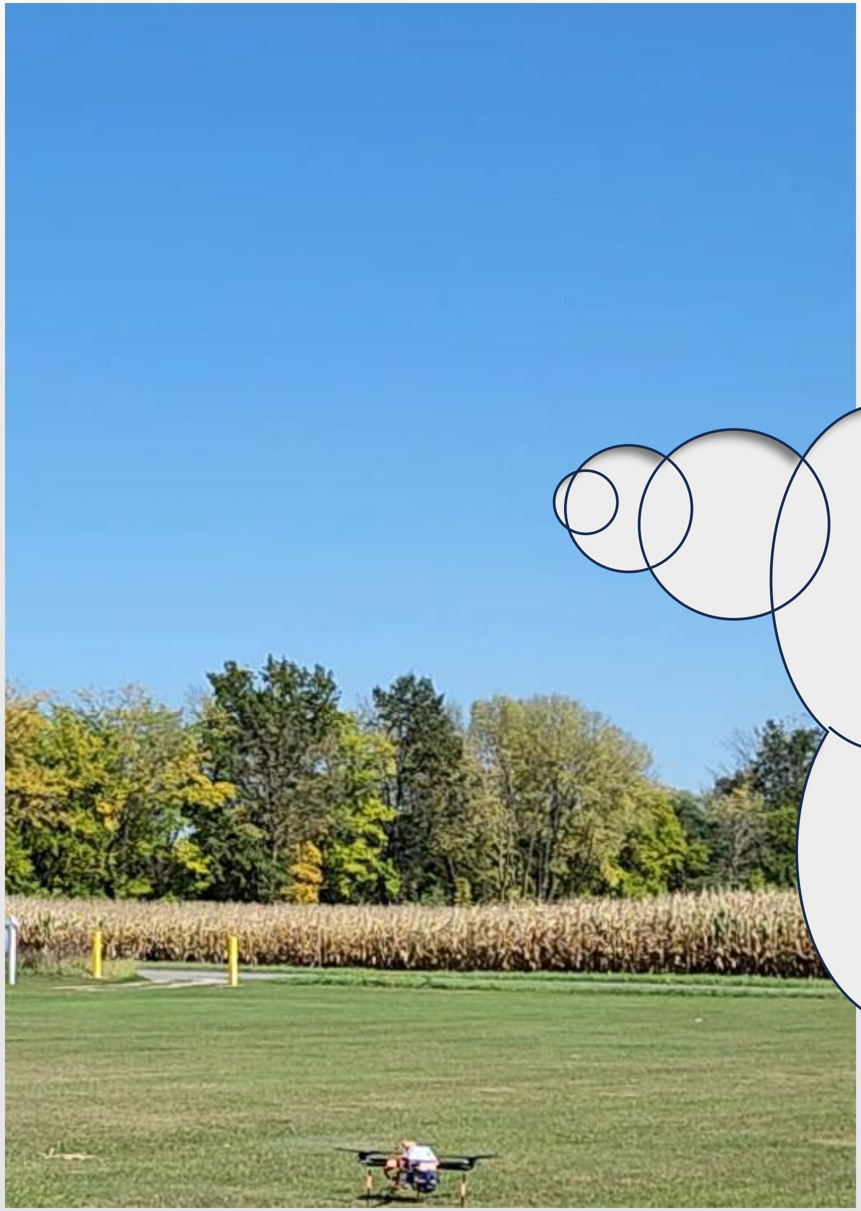
The cause of the crash was not obvious at all. Engineers from our team, Griffiss airbase, and NASA deeply analyzed flight logs.

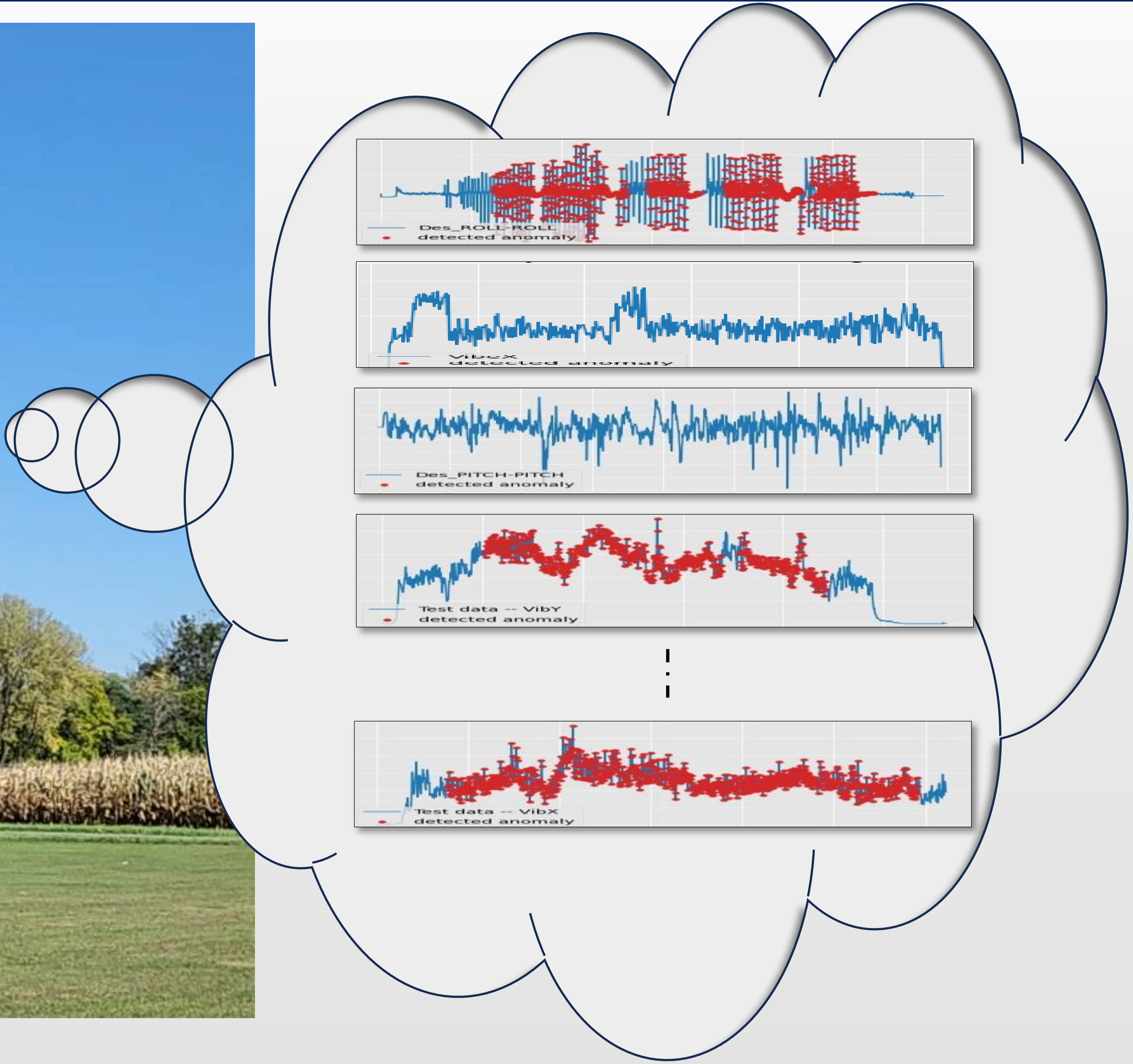
Flight log:
https://tinyurl.com/TEAL-Crash

- Cruise Altitude: 100 ft (30.4 m)
- Distance: 500 meters
- Max Alt: 129.41 meters

Anomaly Detection

Anomaly Detection





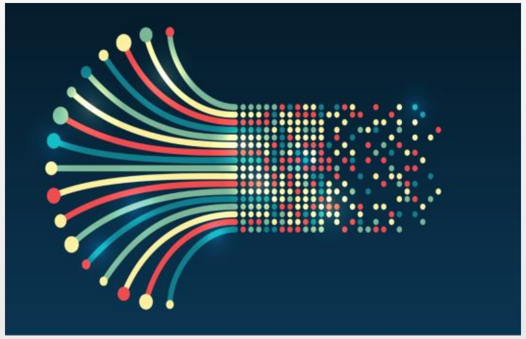
The flight controller collects huge amounts of data using its sensors during the flight

Each flight generates more than 2000 time-series in real time!

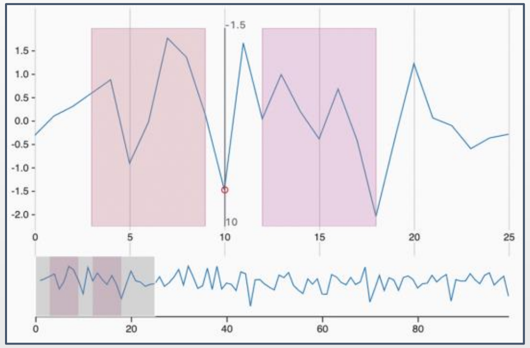
This data is also stored in the flight log

Anomaly Detection - Challenges

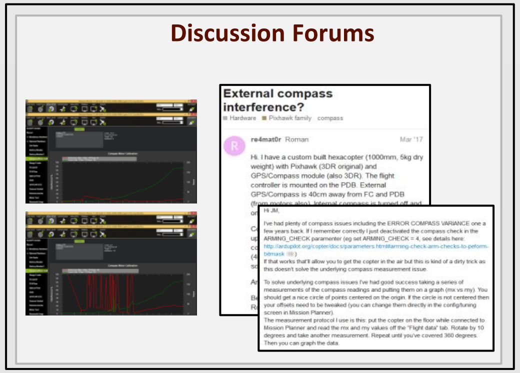
Limited knowledge in documentations



Huge amounts of generated time-series data



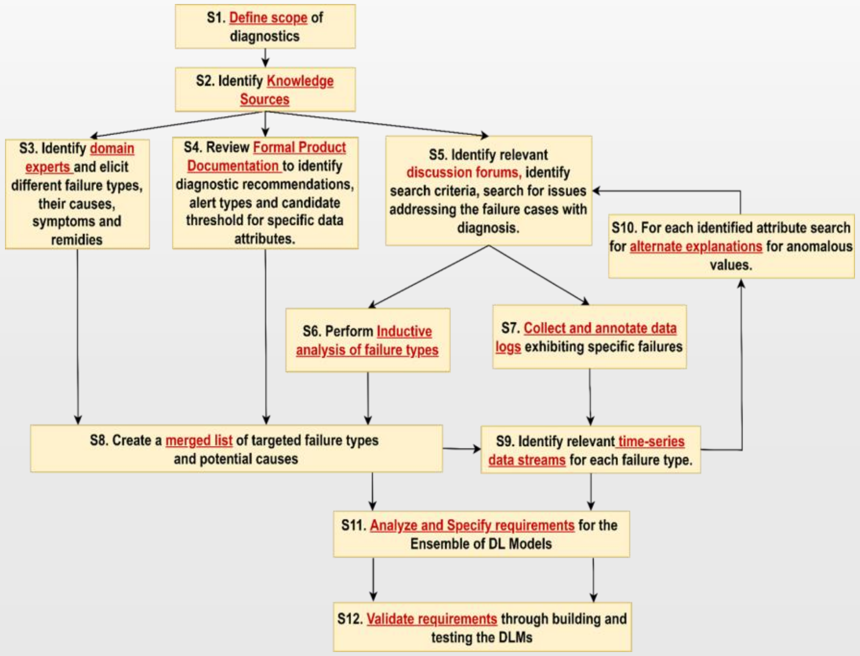
Lack of annotated data



Most of the information shared over the discussion forums

Fuzzy decision boundaries between anomalies and non-anomalies

RESAM

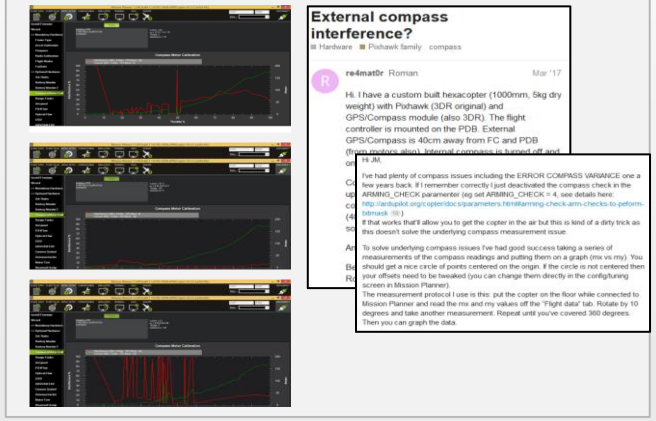


***RESAM:* Requirements Elicitation and Specification for Anomaly Models**

Formal Documentation

Mission Planner and ArduPilot documentation list several different failure types.

Online Discussion Forums



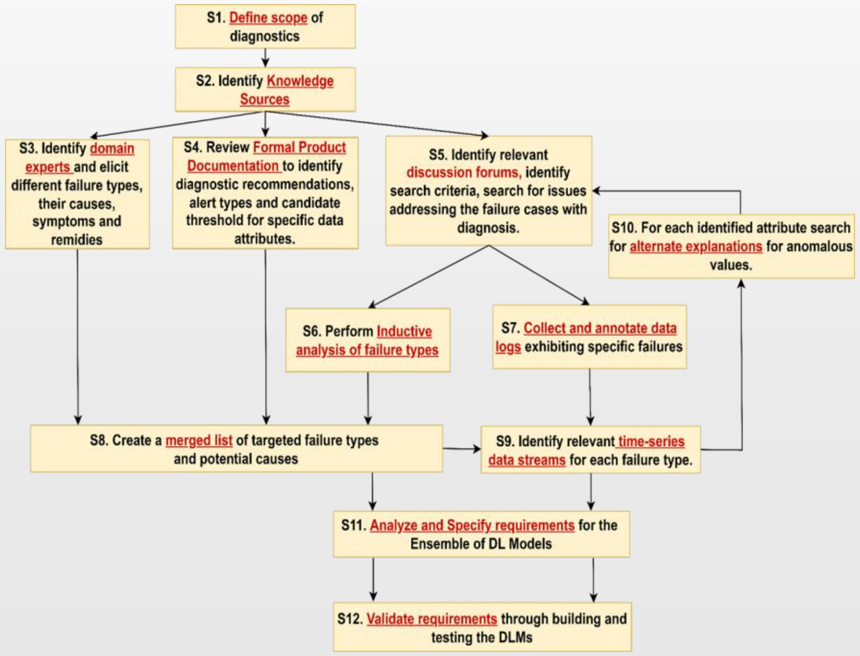
1 ***Identified Sources of Information***

Fault Type	Source			Forum Issues			Fault Description
	CP	SC	FM	ArduP	Px4	Tot.	
Mechanical Failure	●			26	17	43	Divergence of actual vs. planned attitude, PWM imbalance, elevated throttle
Excessive Vibration	●			18	23	41	High fluctuations in sensor readings
Compass Interference	●			17	7	24	Erroneous compass heading
Power Issues	●	●		13	3	16	Unusual fluctuations in battery voltage, complete power failure, brown outs
GPS Failures	●	●		6	7	13	GPS Glitch, Need 3D Fix, Bad velocity, High GPS HDOP
Failsafe Errors	●			8	5	13	Unexpected behavior often triggered by failsafe, Incorrect failsafes
Barometer Failures		●		3	3	6	Barometer not healthy, Alt Disparity
Compass Failures		●		7	5	12	Compass not healthy or not calibrated, Offsets too high, Compasses inconsistent
Inertial Navigation Sys (INS)		●		3	4	7	Accels and/or Gyros not healthy, incorrectly calibrated, or inconsistent
Tuning errors			●	10	6	16	Uncontrolled oscillations in control signal
EKF switching			●	4	0	4	Switching of primary EKF during flight
Voltage sensor calibration			●	3	2	5	Erroneous voltage readings during flight
Logging issue			●	3	1	4	logging inconsistent or stopped
Disarming Errors			●	0	4	4	Problems in disarming
Radio Controller			●	2	1	3	RC not calibrated, RC Low voltage

2 ***Identified the Common Flight Failures***

Islam et al, "RESAM: Requirements Elicitation and Specification for Deep-Learning Anomaly Models with Applications to UAV Flight Controllers," 2022 IEEE 30th International Requirements Engineering Conference (RE), Melbourne, Australia, 2022, pp. 153-165.

RESAM



RESAM: **R**equirements **E**licitation and **S**pecification for **A**nomaly **M**odels

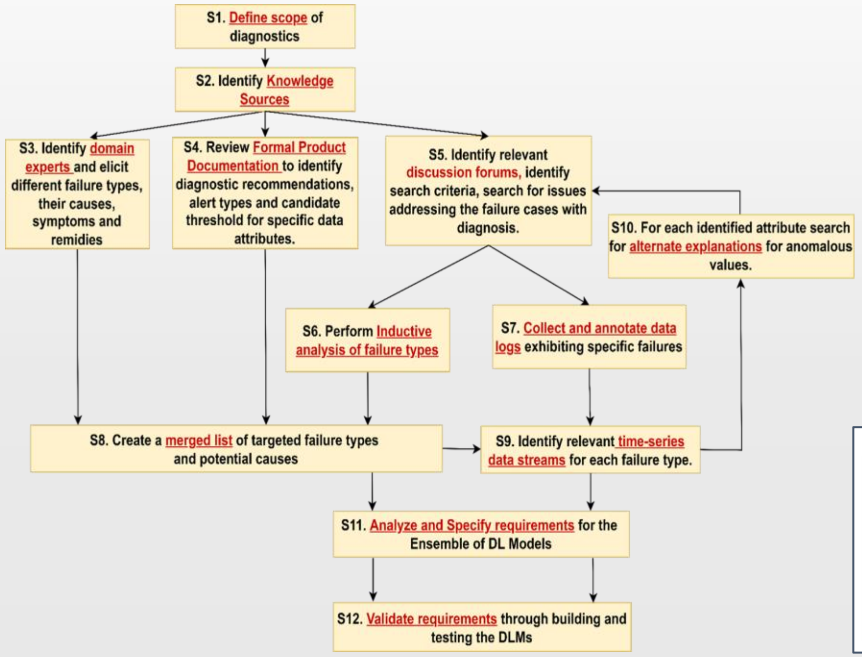
	Description	ArduPilot	PX4 messages
Mechanical	**Actual Attitude**: represented by roll, pitch, and yaw in degrees	ATT.Roll, ATT.Pitch, ATT.Yaw	vehicle_attitude_estimate
	Desired Attitude: represented by roll, pitch, and yaw in degrees	ATT.DesRoll, ATT.DesPitch, ATT.DesYaw	vehicle_attitude_setpoint
	Actual Attitude Rates to compensate for difference in actual and desired attitude (degrees/sec)	PIDR.Act PIDP.Act PIDY.Act RATE (for some old versions)	vehicle_angular_velocity
	Desired Attitude Rates needed to compensate for difference in actual and desired attitude (degrees/sec)	PIDR.Tar PIDP.Tar PIDY.Tar	vehicle_rates_setpoint
	PWM outputs to power ESCs/motors (Typically set between 1100 to 1900)	RCOUT	actuator_outputs
Vibration	**Vibration measures**: Standard deviations of accelerometer measurements (typically values under 30 are acceptable)	VIBE.VibeX, VIBE.VibeY, VIBE.VibeZ, VIBRATION.vibration{_x,_y_z}^{T}	N/A
	Raw accelerometer values: PID outputs from rate controller sent to the mixer to generate PWM outputs	IMU.AccX, IMU.AccY, IMU.AccZ	vehicle_acceleration
	Actuator controls	RCIN	actuator_controls
Compass Error	**Throttle**: Shows generated throttle signal	CTUN.{ThO,Thl}, CURRENT.thr, RCIN.C3, VFR_HUD.throttle, actuator_ controls.control ^{T}	actuator_controls.control
	Raw magnetic field measurements: across x,y, and z axes	MAG.MagX, MAG.MagX, MAG.MagZ,	vehicle_magnetometer sensor_mag
	Norm of magnetic field: considering raw values across x,y, & z axes	CUSTOM.mag_field^T	N/A
Power	**Battery Voltage**	BAT.Volt CURR.Volt	battery_status.voltage_v
	Board Voltage: received at the board	POWR.Vcc, CURR.Vcc, HWSTATUS.Vcc^T	N/A
	Battery Current: drawn from the battery	BAT.Curr CURR.Curr	battery_status.current_c
GPS	**Satellites**: Number of satellites visible to receiver	GPS.NSats	sensor_gps.satellites_used satellite_info.count, GPS_RAW_IT.satellites_visible^T
	Dilution of Precision (DOP): Accuracy measure of GPS signal dependent upon the geometry of connected satellites	GPS.HDop GPS.VDop	sensor_gps.hdop sensor_gps.vdop, GPS_RAW_IT.eph^T
	Position accuracy: Standard deviation of horizontal and vertical position error	N/A	sensor_gps.eph sensor_gps.epv

Attribute^T: Attributes sent to ground control station and available in Telemetry log (TLOG). All other attributes stored onboard.

3 ***Identified the time-series data attributes that reflect the failures***

Islam et al, "RESAM: Requirements Elicitation and Specification for Deep-Learning Anomaly Models with Applications to UAV Flight Controllers," 2022 IEEE 30th International Requirements Engineering Conference (RE), Melbourne, Australia, 2022, pp. 153-165.

RESAM



Mechanical Failures		
R1	When the actual roll, pitch, or yaw deviates suddenly and sufficiently from desired roll, pitch, or yaw, then an *attitude divergence* anomaly shall be detected.	
	Sudden divergence of actual attitude (roll, pitch, yaw) from desired attitude.	ATT.Roll, ATT.Pitch, ATT.Yaw,ATT.DesRoll, ATT.DesPitch, ATT.DesYaw
R2	When an imbalance is detected in RPM sent to the motors then an *RPM imbalance* anomaly shall be detected.	
	Imbalanced RPM sent to motors	RCOUT
Alternate Causes of Symptoms		
1	Severe wind	
2	Twitch maneuvers of the UAV (e.g., for collision avoidance).	

(a) Vibration Problems

R1	When the deviation between GPS readings and estimated position exceeds $30ms^{-2}$ on any axis (X,Y,Z), then a *geolocation* anomaly shall be detected.	
	Standard deviation of accelerometer measurements across three axes.	VIBE.VibeX, VIBE.VibeY and VIBE.VibeZ
R2	When the accelerometer reaches its maximum limit more then 100 times during a mission with increasing frequency, then an 'overworked accelerometer' error shall be detected.	
	Accelaratometer frequently reaching maximum limit	VIBE.Clip0, VIBE.Clip1 and VIBE.Clip2
Alternate Causes of Symptoms		
1	Aging and/or underpowered battery	
2	Excessive wind.	
3	Tuning error (e.g., MOT_THST_HOVER not set correctly)	

(c) Compass Interference

R1	When the a correlation above 30% between the throttle and magenetometers occurs, a *compass interference* anomaly shall be detected.	
	Increased throttle interferes with compass (detected by correlation between magnetometer readings and throttle)	l2-norm (i.e.,$\sqrt{SumOfMags}$, where SumOfMags=$MagX^2 + MagY^2 + MagZ^2$) Throttle (CTUN.ThO)
No known alternate causes of symptoms		

(b) GPS Glitch

R1	When GPS.HDop values exceed 2 a 'GPS Glitch with Loss of horizontal precision' error shall be raised.	
	Number of satellites Loss of GPS precision.	NSats GPS.HDop
R2	When GPS.HDop values exceed 2 and sudden and sharp course corrections are detected, then a 'GPS Geolocation Failure' shall be raised.	
	Sharp flight route divergence Number of satellites Loss of GPS precision.	GPS Coordinates NSats GPS.HDop
Alternate Causes of Symptoms		
1	Loss of satellite lock	
2	Incorrect positioning of components on UAV causing interference	

(d) Power Issues

R1	When increases in throttle are correlated with battery drain then a 'throttle causing excessive battery drain' error is detected.	
	Increases in throttle correlated with battery drain	CTUN.Tho, BAT.Volt
R2	When erratic swings in altitude are detected then an 'altitude fluctuation' error is detected.	
	Erratic swings in altitude	BARO.Alt, CTUN.Alt, GPS.Alt
Alternate Causes of Symptoms		
1	Excessive wind.	
2	Onboard software or sensor drain	

RESAM: **R**equirements **E**licitation and **S**pecification for **A**nomaly **M**odels

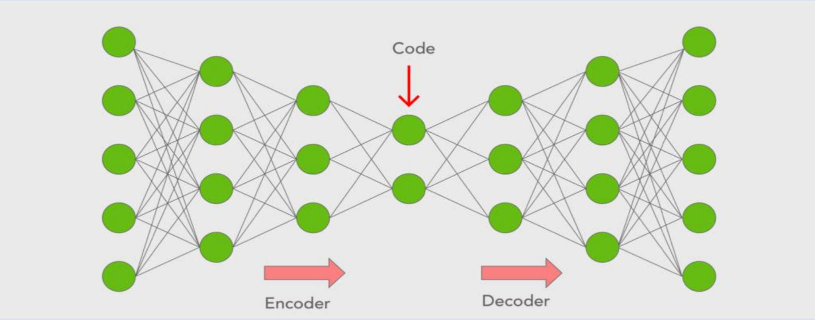
4

Specified software requirements for building Deep Learning-based anomaly detectors for detecting FIVE flight failures.

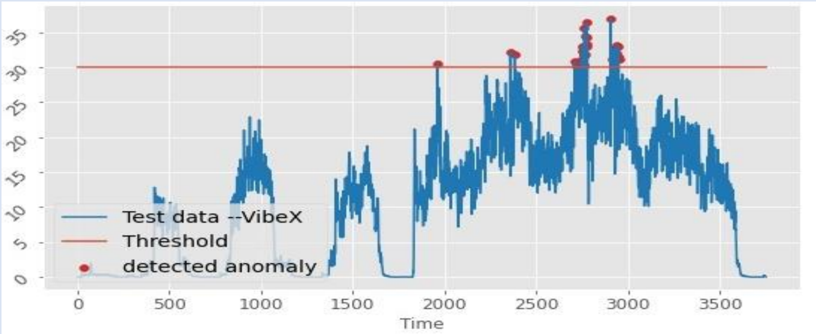
Islam et al, "RESAM: Requirements Elicitation and Specification for Deep-Learning Anomaly Models with Applications to UAV Flight Controllers," 2022 IEEE 30th International Requirements Engineering Conference (RE), Melbourne, Australia, 2022, pp. 153-165.

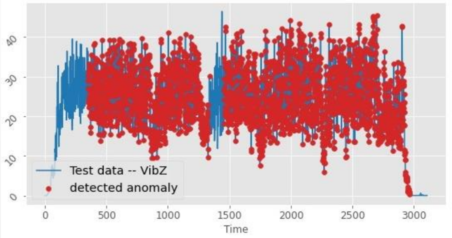
RESAM

LSTM Autoencoders
(Deep Learning Approach)

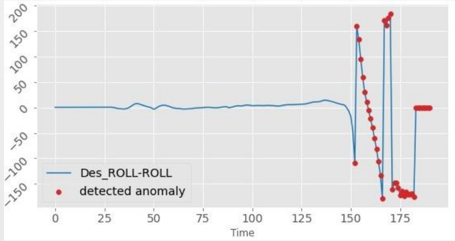


Rule-based Methods

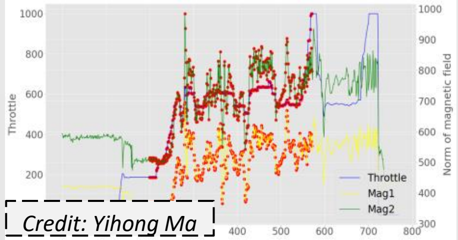




Vibration Anomaly



Attitude Anomaly



Credit: Yihong Ma

Interference Anomaly

Count of annotated training logs collected from our own UAVs

Type	Attitude					
	Our own logs			Forum logs		
	Total	Norm.	Anom.	Total	Norm.	Anom.
Quadcopters	69	48	21	29	15	14
Hexcopters	43	28	15	17	7	10
Total	112	76	36	46	22	24

Type	Vibration					
	Our own logs			Forum logs		
	Total	Norm.	Anom.	Total	Norm.	Anom.
Quadcopters	103	52	51	29	15	14
Hexcopters	32	16	16	17	7	10
Total	135	68	67	46	22	24

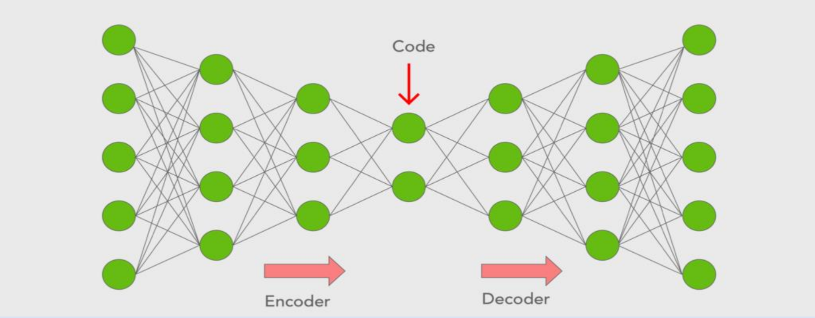
Type	Compass Interference					
	Our own logs			Forum logs		
	Total	Norm.	Anom.	Total	Norm.	Anom.
Quadcopters	38	30	8	16	10	7
Hexcopters	0	0	0	4	0	3
Total	38	30	8	20	10	10

5 ***Used the requirements to design LSTM Autoencoders for detecting THREE of these failures.***

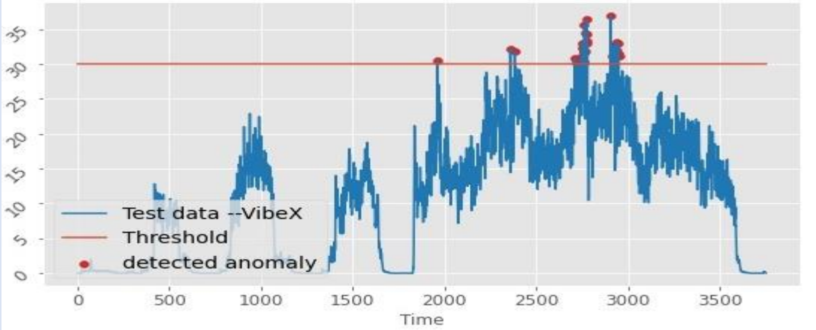
Islam et al, "RESAM: Requirements Elicitation and Specification for Deep-Learning Anomaly Models with Applications to UAV Flight Controllers," 2022 IEEE 30th International Requirements Engineering Conference (RE), Melbourne, Australia, 2022, pp. 153-165.

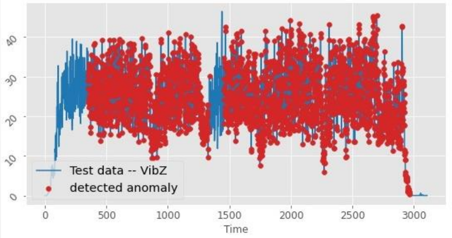
RESAM

LSTM Autoencoders
(Deep Learning Approach)

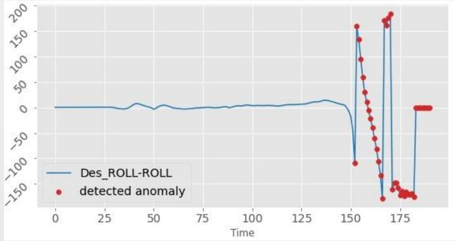


Rule-based Methods

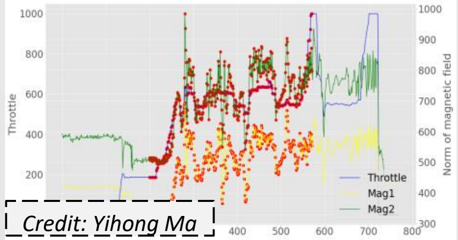




Vibration Anomaly



Attitude Anomaly



Credit: Yihong Ma

Interference Anomaly

Tested on 46 publicly available flight logs collected from forums

	Metrics	Vibration			Attitude			Int
		VibeX	VibeY	VibeZ	Roll	Pitch	Yaw	Mag
LSTM	Precision	0.68	0.61	0.86	0.81	0.90	0.83	0.71
	Recall	1.00	1.00	0.95	0.87	0.75	0.63	1.00
	Accuracy	0.87	0.80	0.91	0.89	0.91	0.91	0.80
	F1	0.81	0.76	0.90	0.84	0.82	0.71	0.83
Rule	Precision	0.67	1.00	0.88	0.78	0.83	0.47	0.53
	Recall	0.15	0.35	0.79	0.47	0.42	0.86	0.80
	Accuracy	0.74	0.80	0.87	0.78	0.82	0.80	0.75
	F1	0.25	0.53	0.83	0.58	0.56	0.61	0.64

Metrics	Vibration			Attitude			Mag Int.
	VibeX	VibeY	VibeZ	Roll	Pitch	Yaw	Mag
LSTM	0.919	0.906	0.958	0.928	0.866	0.817	0.750

Area under the curve (AUC)

5 ***Used the requirements to design LSTM Autoencoders for detecting THREE of these failures.***

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Problems with Deep Learning Detectors

Vehicle Type: Hexacopters
Flight Control Computer: mRo Control Zero F7
Flight Control Software: PX4 Autopilot
Companion Computer: NVIDIA Jetson (NX)

Heuristic Based Anomaly Detectors

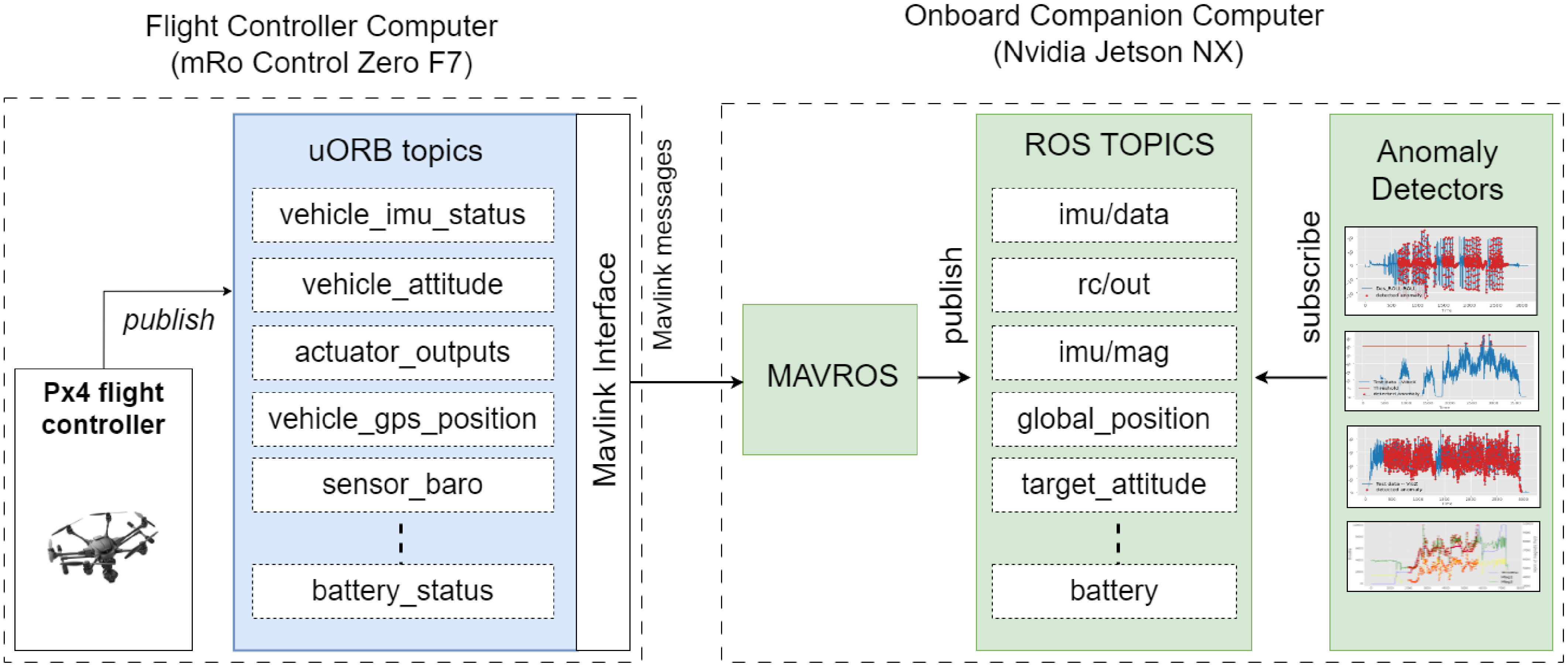
Heuristic Based Detectors

7 Heuristic Based Anomaly Detectors

Symptom	Ardupilot		Px4	
	Attributes	**Anomaly conditions**	**Attributes**	**Anomaly conditions**
Vibration	VIBE.{VibeX,VibeY,VibeZ}	values over $30ms^2$	sensor_accel	Standard deviation over $30ms^2$
Attitude	ATT.{Roll,Pitch,Yaw} ATT.Des{Roll,Pitch,Yaw}	ATT.{Roll,Pitch,Yaw} diverges from ATT.Des{Roll,Pitch,Yaw} by 5°	vehicle_attitude vehicle_attitude_setpoint	vehicle_attitude diverges from vehicle_attitude_setpoint by 5°
Interference	CTUN.ThO MAG.{MagX,MagY,MagZ}	Correlation between norm of MAG and ThO goes over 50%	sersor_mag.{x,y,z} actuator_control[3]	Correlation between norm of sersor_mag and actuator_control[3] goes over 50%
GPS	GPS.NSats GPS.HDop	NSats under 12 and HDop over 1.2	vehicle_gps_position.{ satellites_used,hdop,vdop, noise,jamming_indicator}	satellites_used<12, hdop>1.2m vdop>2m, noise>120 jamming_indicator>40
Power	BAT.Curr BAT.Volt	Slope of Curr or Volt below -0.05 in any 200 observation window	battery_status.voltage_v battery_status.current_a	Slope of current_a or voltage_v below -0.05 in any 200 observation window
Rc-in-out	RCOU.{C1:C6 }	Avg. gap above 200 PWM between two sets of RCOU.C values, RCOU.C clips the minimum or maximum PWM values	actuator_outputs[0:5]	Avg. gap above 200 PWM between two sets of actuator_outputs values, actuator_outputs clips the minimum or maximum PWM values
EKF	EKF3.{IP,IV,IM } EKF4.{SP,SV,SM,SH,SVT}	EKF3.{IP,IV} outside range [-1,1] EKF3.{IM} outside range [-50,50] EKF4 outside range[-0.5,0.5]	estimator_innovations[:]	Any innovation outside range [-1,1]

Islam et al., "Diagnosing and Explaining Flight Anomalies in small Un-manned Aerial Systems", ACM Transaction on Cyber-Physical Systems (Work complete, To be submitted)

Real-Time, Onboard Architecture

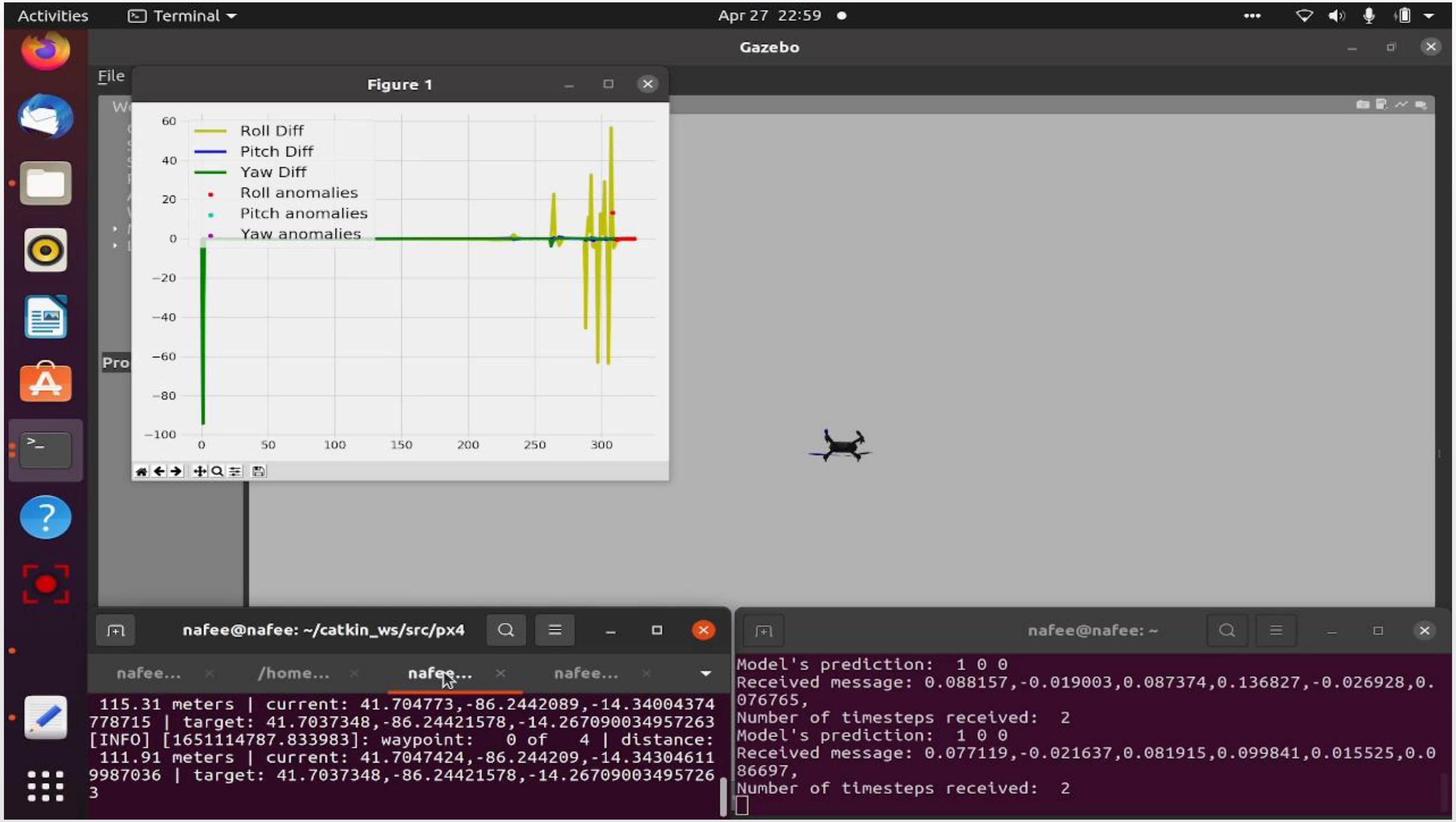


Using MAVROS to communicate with PX4 and then subscribe to ROS Topic

Islam et al., "Diagnosing and Explaining Flight Anomalies in small Un-manned Aerial Systems", ACM Transaction on Cyber-Physical Systems (Work complete, To be submitted)

Real World Flight Tests

Test in Gazebo Simulator



Simulating anomaly detection in Gazebo, a high-fidelity simulator.

Attitude anomaly was forced using high wind gusts in Gazebo.

Islam et al., "Diagnosing and Explaining Flight Anomalies in small Un-manned Aerial Systems", ACM Transaction on Cyber-Physical Systems (Work complete, To be submitted)

Field Test with Real Drones – Passing Criteria

Detectors	ROS Topics	Passing Criteria
Vibration	/mavros/imu/data	(1) Vibration data recorded by the real-time detectors match the data found in the logs. (2) Detection of intentionally (and carefully) generated vibrations using heavy payload.
Attitude	/mavros/imu/data /mavros/setpoint_raw/target_attitude	(1) Attitude divergence values recorded by the real-time detectors match the data found in the logs. (2) Inducing attitude divergence by temporarily restricting roll/pitch/yaw movements and ensuring that attitude anomalies are detected when divergence goes over threshold.
Interference	/mavros/imu/mag /mavros/setpoint_raw/target_attitude	(1) Interference data (mag and throttle) recorded by the real-time detectors match the data found in the logs. (2) Lowering the detection threshold for interference and ensuring that the interference detection warnings are generated when the correlation between magnetic field and throttle goes higher than the threshold
GPS	/mavros/gpsstatus/gps1/raw	(1) GPS data recorded by the real-time detectors match the data found in the logs. (2) Detection of low number of satellites and high HDOP and VDOP inside GPS constrained area (e.g., confined laboratory)
Power	/mavros/battery	(1) Power data recorded by the real-time detectors match the data found in the logs. (2) Performing battery endurance tests and ensuring that low battery warnings are raised when battery voltage falls below predefined thresholds
RC Output	/mavros/rc/out	
EKF	/mavros/estimator_status	[illegible] found in the logs.

(1) When RC output values recorded by the real-time detectors match the data found in the logs. (2) Detection of intentionally generated RC clippings using heavy payload.

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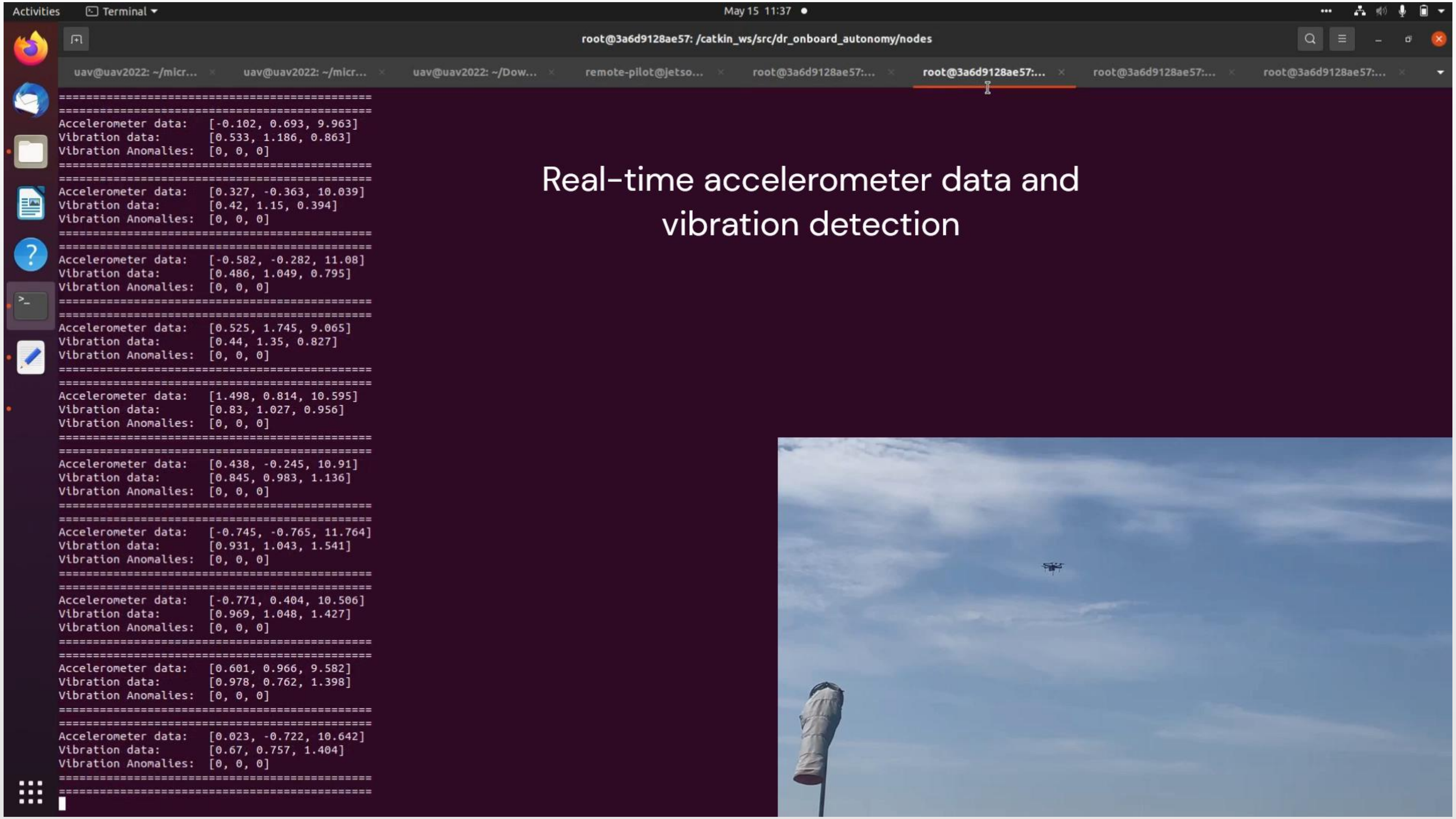
Field Test with Real Drones

Tests were conducted against a simple takeoff, fly to waypoint A, return to waypoint B, Land.

This drone was equipped with **a step-down transformer causing imbalance**. It was deliberately selected for the tests.

Islam et al., "Diagnosing and Explaining Flight Anomalies in small Un-manned Aerial Systems", ACM Transaction on Cyber-Physical Systems (Work complete, To be submitted)

Field Test with Real Drones



Analysis is run onboard and results streamed to the Ground Station.

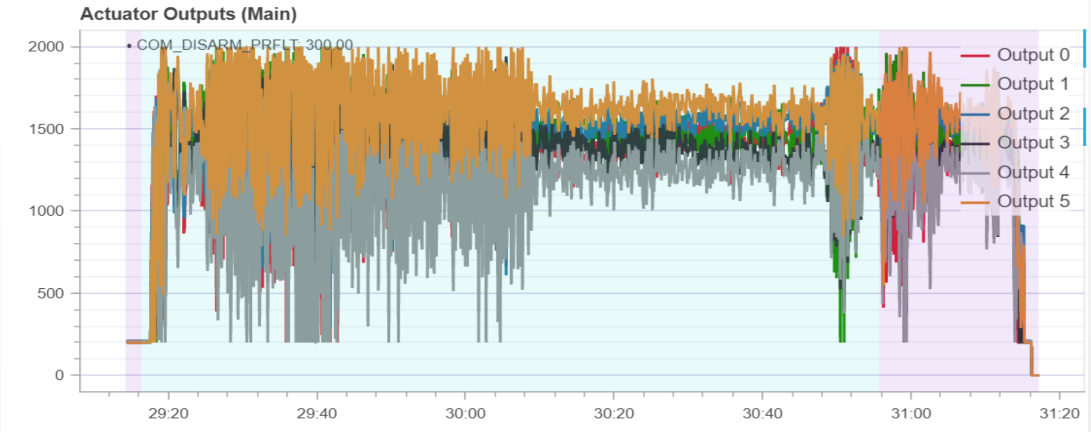
Real-time onboard detection of Vibration, Attitude and Motor PWM output anomalies

Islam et al., "Diagnosing and Explaining Flight Anomalies in small Un-manned Aerial Systems", ACM Transaction on Cyber-Physical Systems (Work complete, To be submitted)

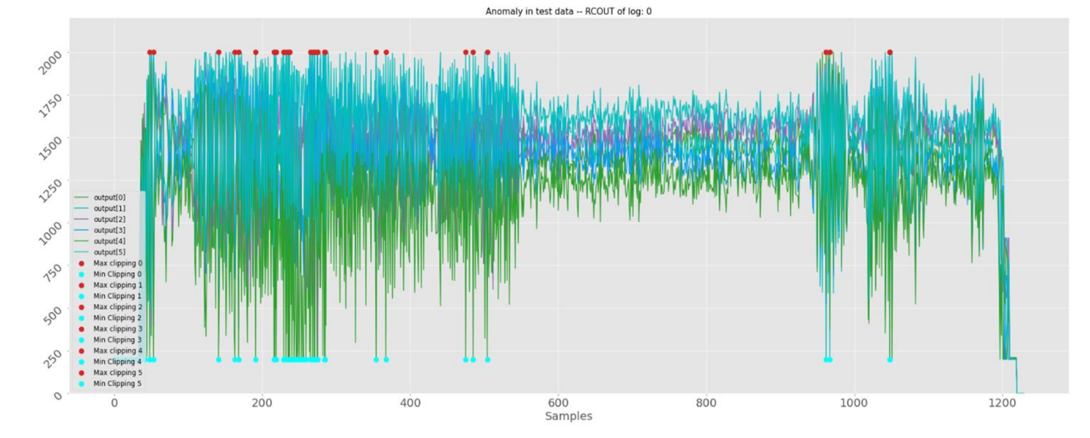
Field Test with Real Drones - Results

```
Motor PWM values:  [1799.  766. 1928.  456.  199. 1999.]
Minimum clipping anomalies:  [0, 0, 0, 0, 1, 0]
Maximum clipping anomalies:  [0, 0, 0, 0, 0, 1]
[1315, 1528, 1451, 1398, 1317, 1525]
Found it
Motor PWM values:  [1315. 1528. 1451. 1398. 1317. 1525.]
Minimum clipping anomalies:  [0, 0, 0, 0, 0, 0]
Maximum clipping anomalies:  [0, 0, 0, 0, 0, 0]
[761, 1921, 977, 1805, 1764, 1042]
Found it
Motor PWM values:  [ 761. 1921.  977. 1805. 1764. 1042.]
Minimum clipping anomalies:  [0, 0, 0, 0, 0, 0]
Maximum clipping anomalies:  [0, 0, 0, 0, 0, 0]
[1337, 1537, 1490, 1388, 1251, 1609]
Found it
Motor PWM values:  [1337. 1537. 1490. 1388. 1251. 1609.]
Minimum clipping anomalies:  [0, 0, 0, 0, 0, 0]
Maximum clipping anomalies:  [0, 0, 0, 0, 0, 0]
[1789, 909, 1900, 691, 432, 1998]
Found it
Motor PWM values:  [1789.  909. 1900.  691.  432. 1998.]
Minimum clipping anomalies:  [0, 0, 0, 0, 0, 0]
Maximum clipping anomalies:  [0, 0, 0, 0, 0, 1]
```

Anomalies detected in motor PWM outputs!
Prototype sends alerts to Ground Station Console.



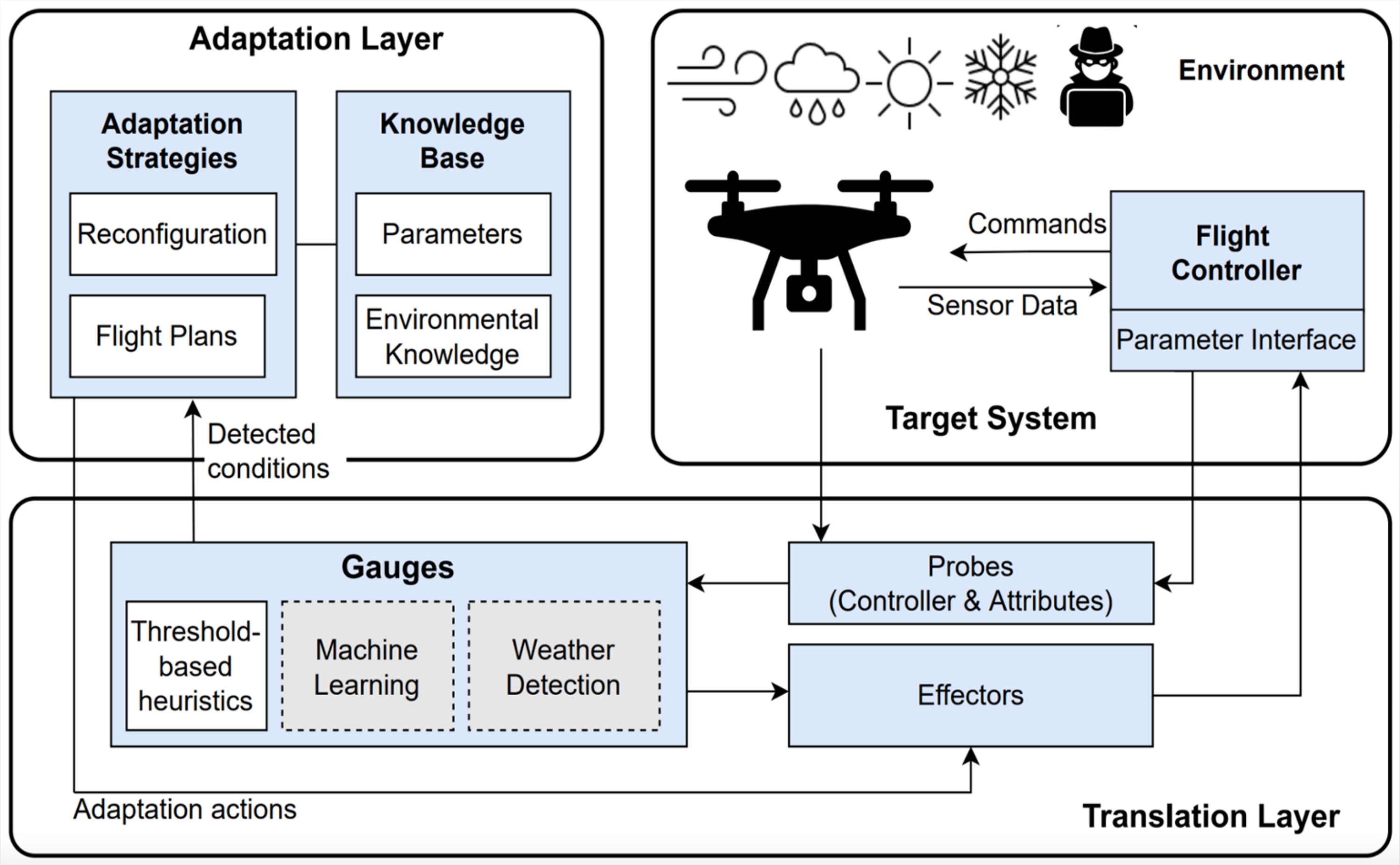
Motor PWM outputs from the flight log



Motor PWM outputs recorded in real-time

Field Test - Detection and Adaptation

***CICADA**: Controller Instability-preventing Configuration Aware Drone Adaptation*



PX4 has 1800 different flight parameters!

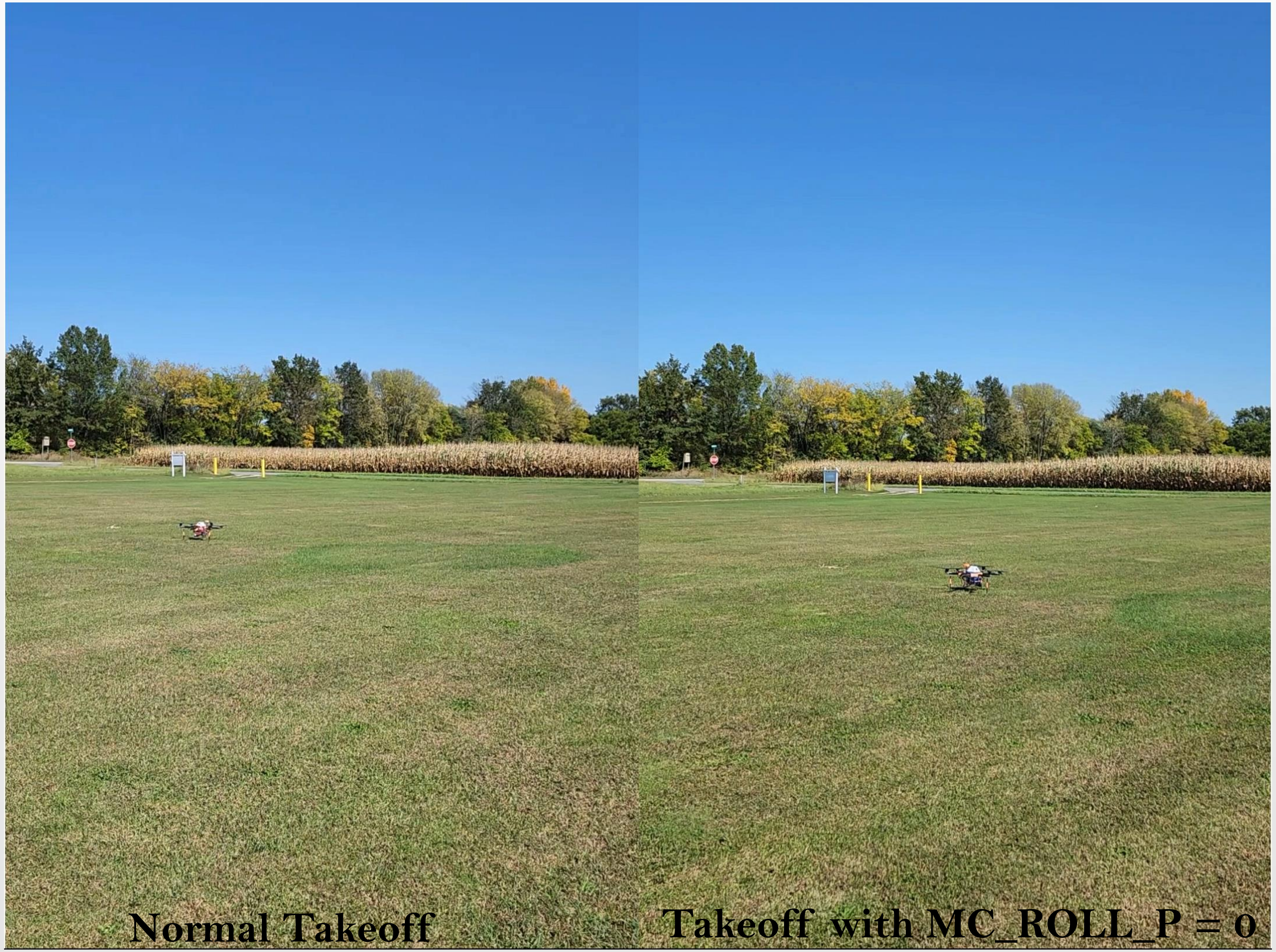
This work explores which parameters are likely to cause instability.

Supported Adaptation:

- Revert-to-baseline
- Loiter
- Land-in-place

*Purandare, **Islam** et al., "Self-Adaptive Mechanisms for Misconfigurations in Small Uncrewed Aerial Systems", Software Engineering for Adaptive and Self-Managing Systems (SEAMS), 2023*

Field Test - Detection and Adaptation



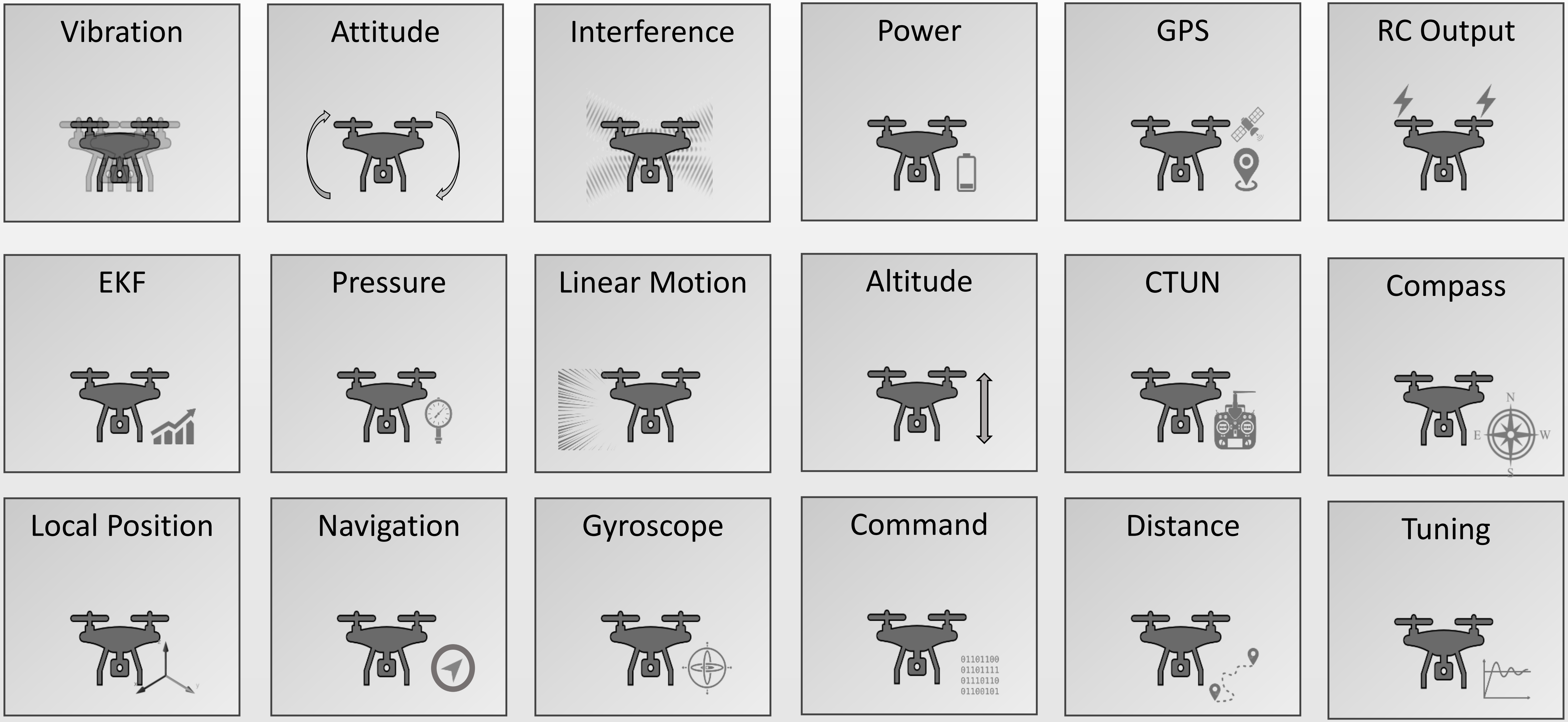
Testing **Revert-to-Baseline** with the CICADA Framework

MC_ROLL_P had a baseline value of 0.4 which we changed to 0.

Upon **anomaly detection**, MC_ROLL_P was ***reverted*** back to the baseline

Resource Optimization for Real-time Analytics

More anomalies ..

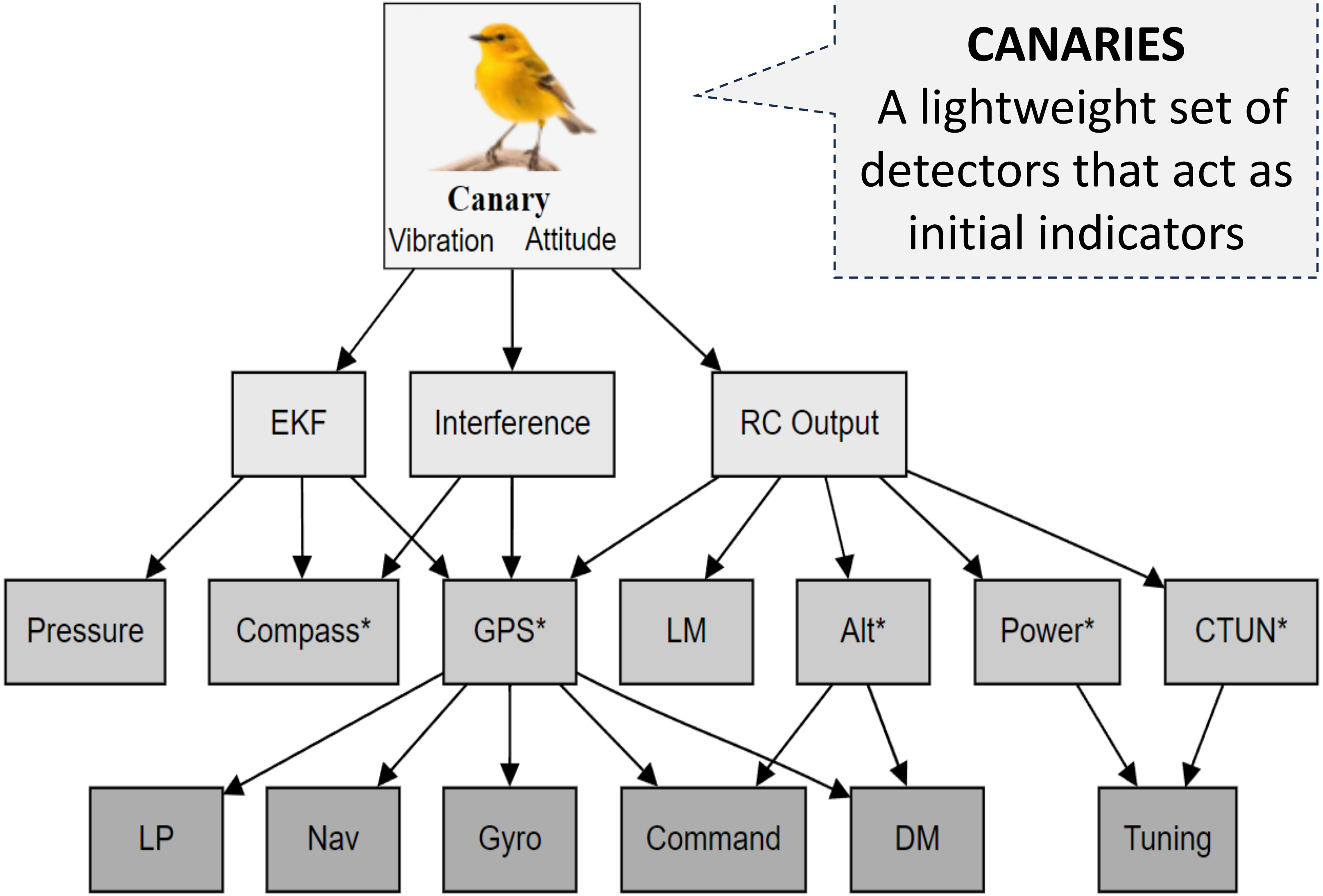


18 anomaly types were identified. Most required analysis of multiple data stream in real-time.

Needed:

Light weight approach that can run in the background all the time, and trigger an alert that activates more refined detectors.

ADAM: Adaptive Drone Anomaly Monitor



CANARIES
A lightweight set of detectors that act as initial indicators

ADAM avoids the requirement to run all the detectors simultaneously.

ADAM turns on anomaly detectors using the **Activation Sequence Tree**.

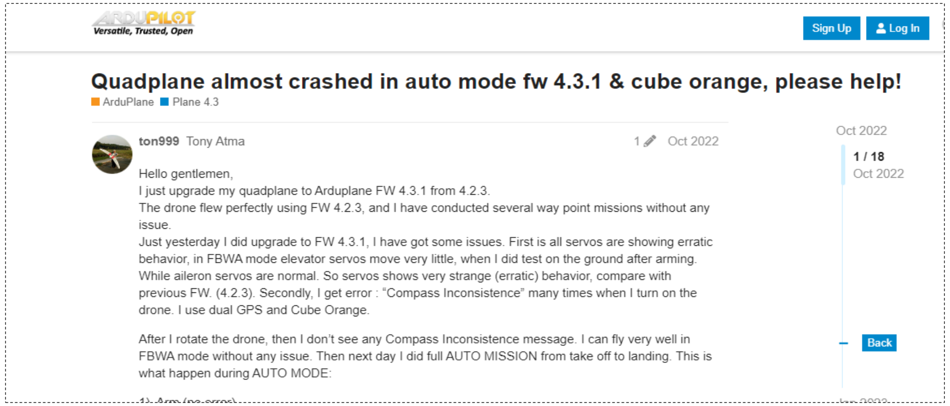
Anomalies detected in a **parent node** turns on all detectors of its **child node**.

Islam et al., ADAM: Adaptive Monitoring of Runtime Anomalies in Small Uncrewed Aerial", Software Engineering for Adaptive and Self-Managing Systems (SEAMS), 2024

ADAM: Adaptive Drone Anomaly Monitor

Detector Turned On

Anomaly Detected

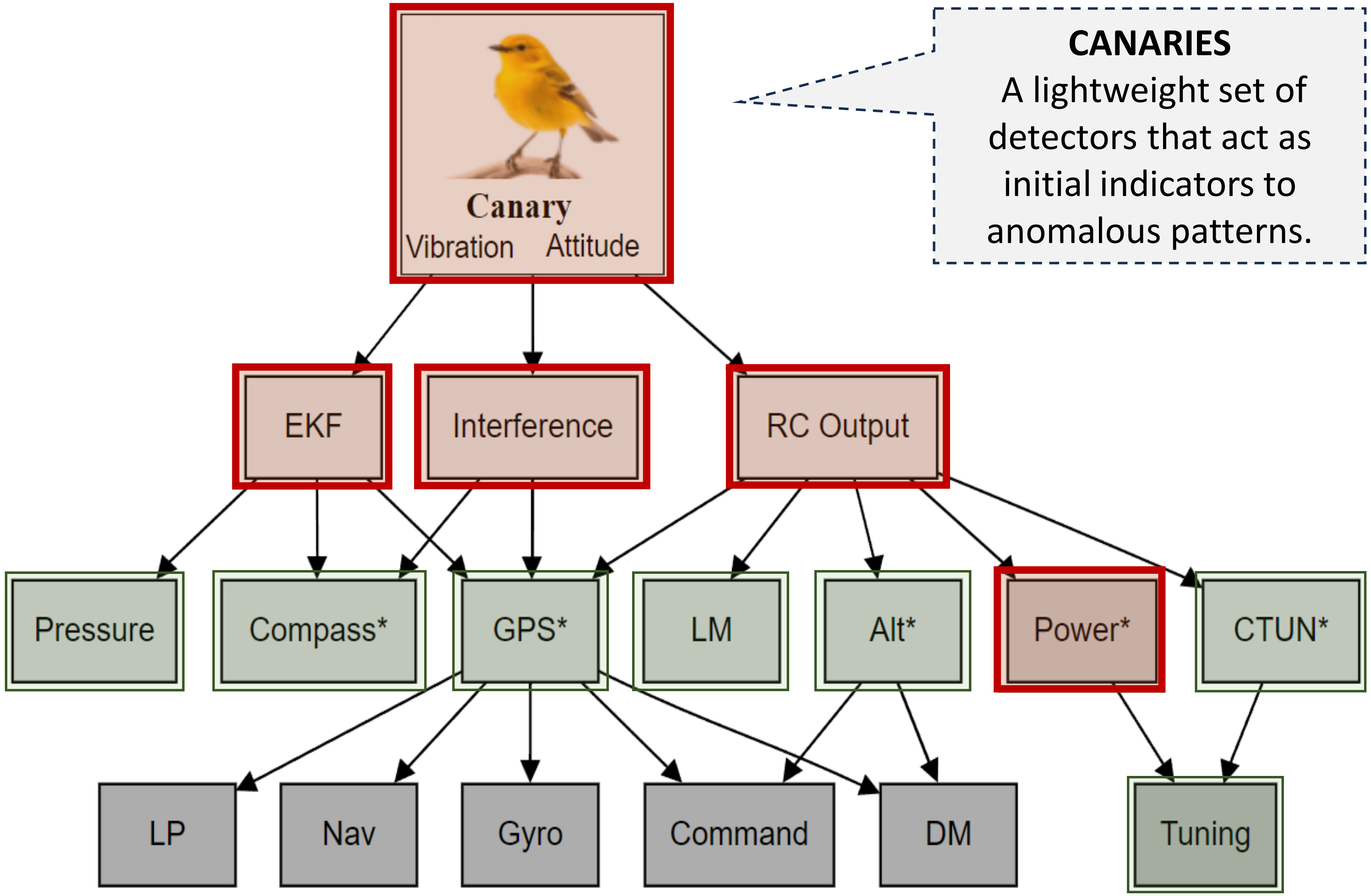

Quadplane almost crashed in auto mode fw 4.3.1 & cube orange, please help!

ArduPlane Plane 4.3

ton999 Tony Atma 1 Oct 2022

Hello gentlemen,
I just upgrade my quadplane to Arduplane FW 4.3.1 from 4.2.3.
The drone flew perfectly using FW 4.2.3, and I have conducted several way point missions without any issue.
Just yesterday I did upgrade to FW 4.3.1, I have got some issues. First is all servos are showing erratic behavior, in FBWA mode elevator servos move very little, when I did test on the ground after arming. While aileron servos are normal. So servos shows very strange (erratic) behavior, compare with previous FW. (4.2.3). Secondly, I get error : "Compass Inconsistence" many times when I turn on the drone. I use dual GPS and Cube Orange.

After I rotate the drone, then I don't see any Compass Inconsistence message. I can fly very well in FBWA mode without any issue. Then next day I did full AUTO MISSION from take off to landing. This is what happen during AUTO MODE:

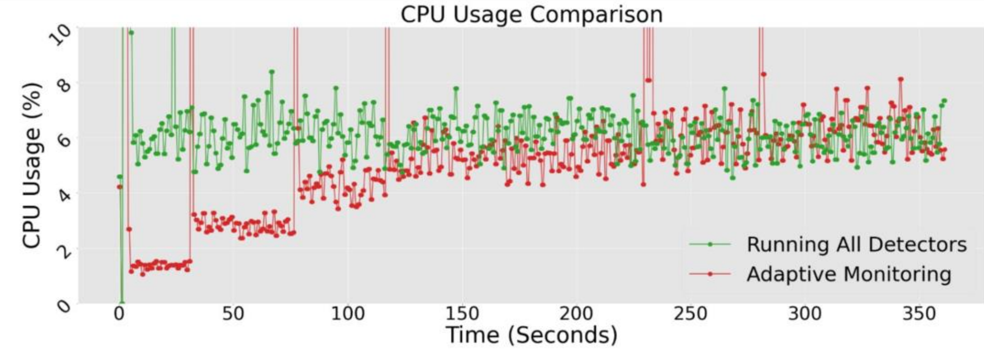


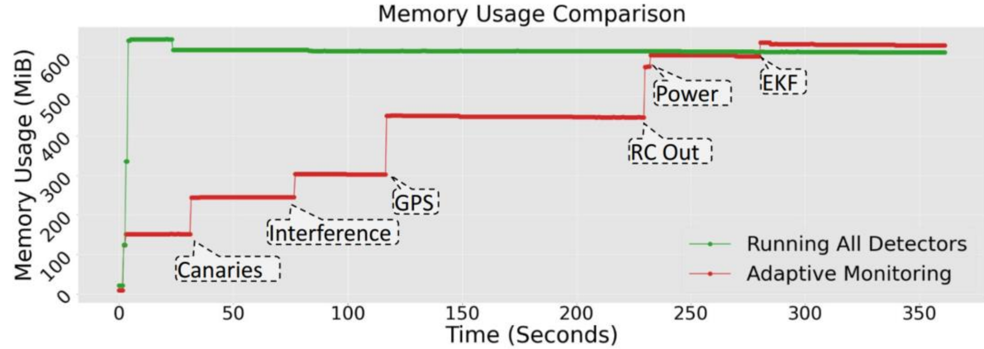
Activation Sequence Tree

Islam et al., ADAM: Adaptive Monitoring of Runtime Anomalies in Small Uncrewed Aerial", Software Engineering for Adaptive and Self-Managing Systems (SEAMS), 2024

Evaluating *ADAM*

Anomaly Count	Case Count	% Detected (Adapt.)	% Traversed	% Detected (Non-Adapt.)	% Crash
1	5	60.00	60.00	100.00	0.00
2	7	78.57	78.57	92.86	28.57
3	6	72.22	83.33	77.78	33.33
4	7	75.00	92.86	75.00	42.86
5	14	88.57	95.71	88.57	50.00
6	12	87.50	98.61	87.50	66.67
7	10	87.14	98.57	87.14	70.00
7+	8	74.24	96.97	74.24	37.50
Total	**69**	**82.51**	**95.04**	**83.97**	**47.83**





Evaluation on forum logs: The adaptive monitoring approach using *ADAM* achieved **82.52%** accuracy on forum logs, almost matching the non-adaptive approach's **83.97%**

Resource consumption test: ADAM could reduce resouce usage by up to ***65%***.

In steady state, when only the Canary remains activated, it could achieve much higher resource consumption savings.

Islam et al., ADAM: Adaptive Monitoring of Runtime Anomalies in Small Uncrewed Aerial", Software Engineering for Adaptive and Self-Managing Systems (SEAMS), 2024

Evaluating *ADAM*

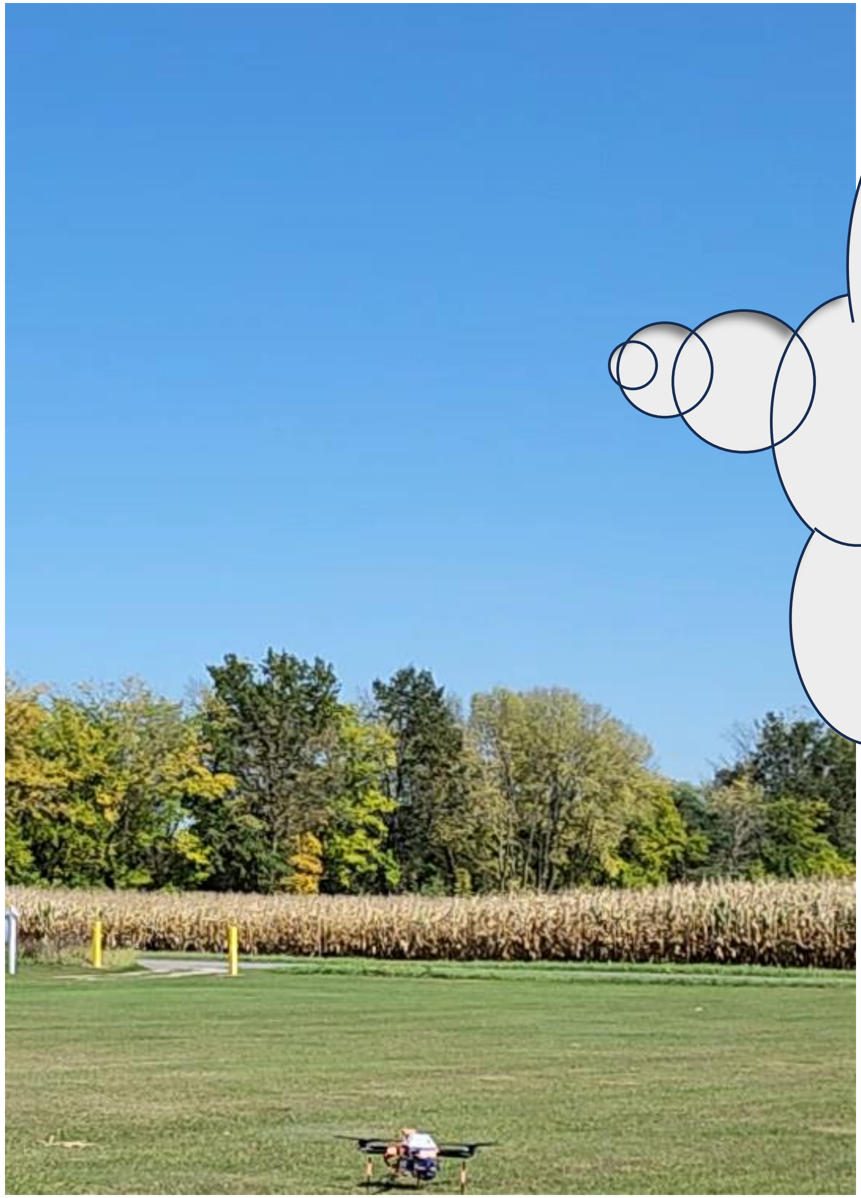
Functionality Test: The functionality of the framework was tested in a high fidelity simulator Gazebo. Pseudo-anomaly messages were sent throughout the mission to trigger various anomaly detectors in the activation sequence tree.

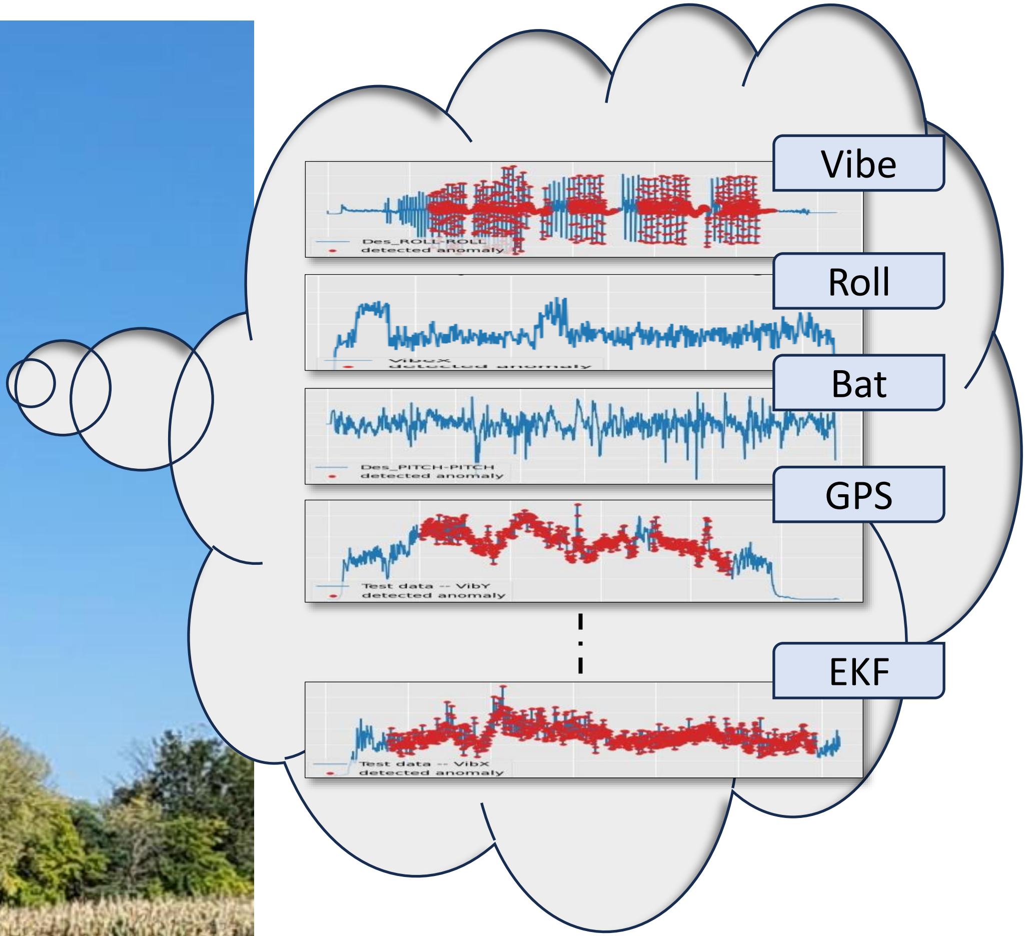
Initial lab testing with real drones: The drone was manually tilted 10 degrees to generate an attitude anomaly, which triggered the Canaries!

Islam et al., ADAM: Adaptive Monitoring of Runtime Anomalies in Small Uncrewed Aerial", Software Engineering for Adaptive and Self-Managing Systems (SEAMS), 2024

Anomaly Diagnosis

Anomaly Diagnosis





Anomaly Detection (Symptoms)

Vibe

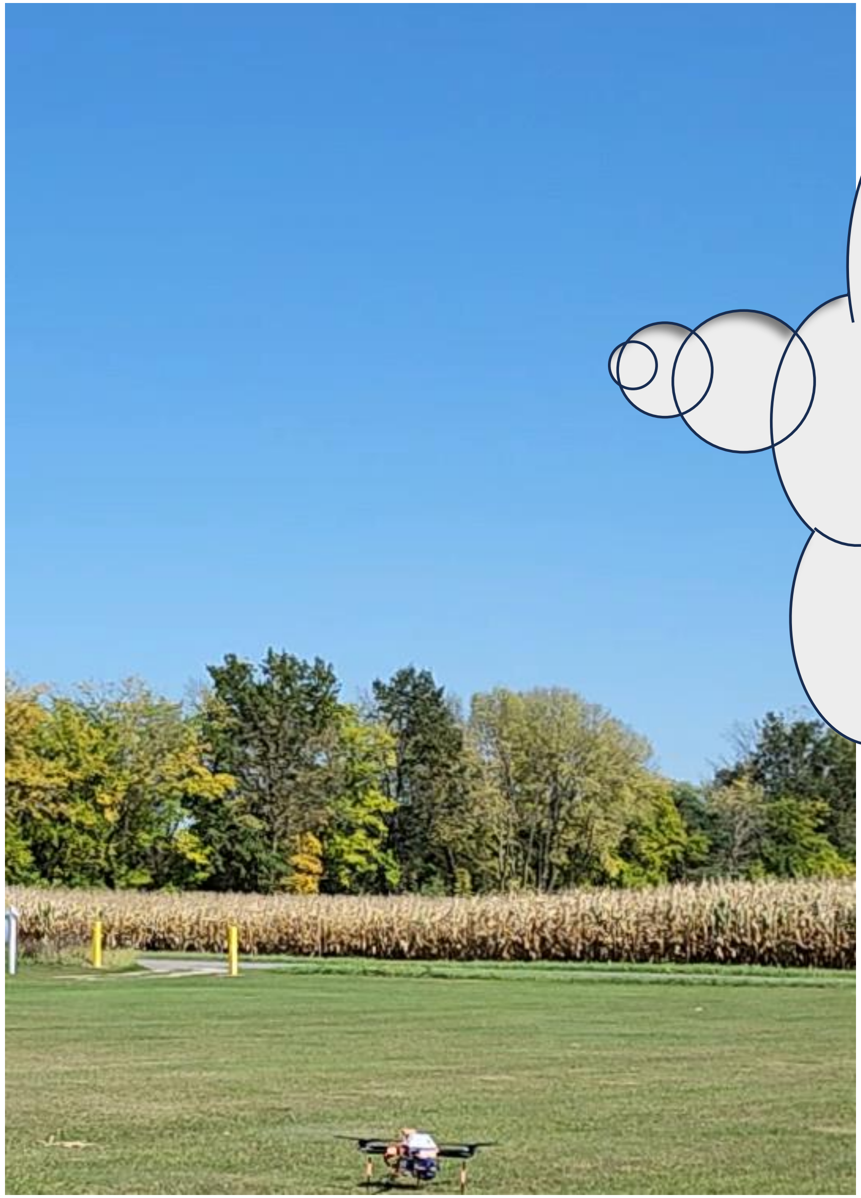
GPS

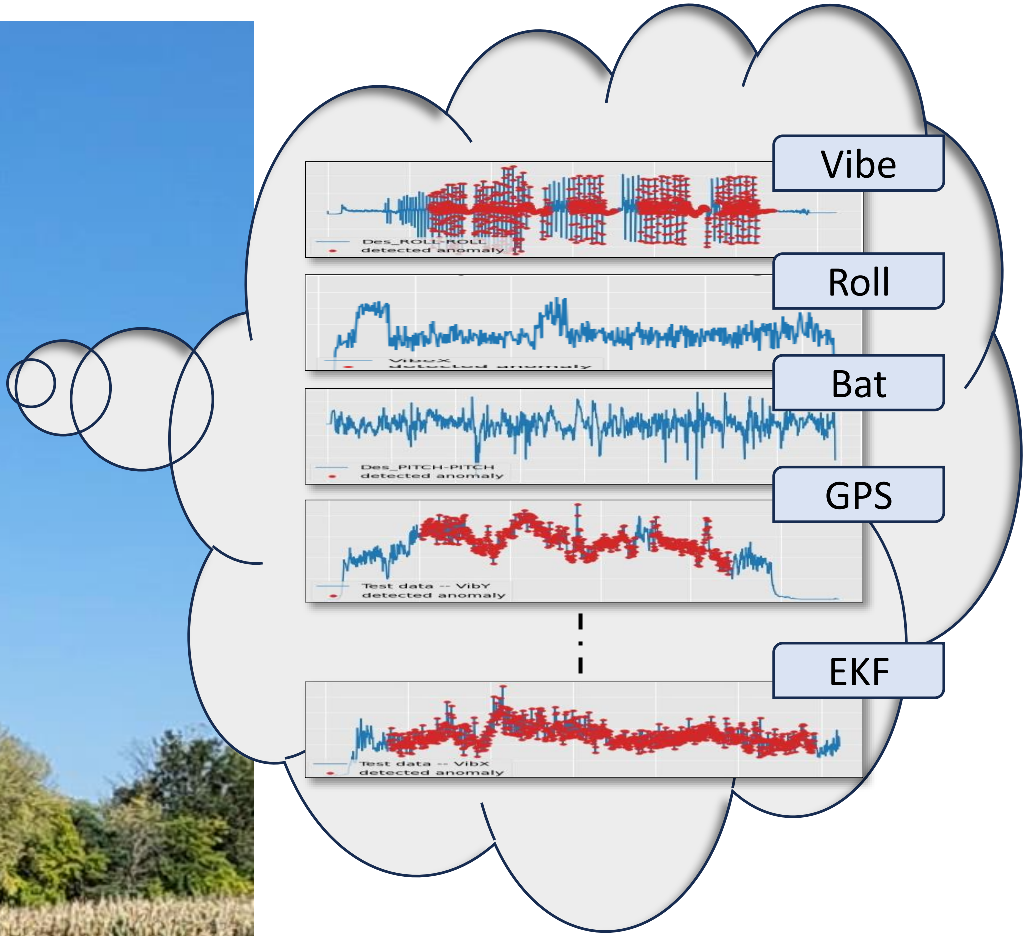
EKF

Symptoms

Type of anomalies reflected in different data attributes

Anomaly Diagnosis





Anomaly Diagnosis

Symptoms

Vibe | GPS | EKF

↓

Root Cause

Hardware Issue | Tuning Issue

Root Cause

The high-level problem that is causing the anomalies in the data attribute(s).

Anomaly Diagnosis

Symptom Identification

21 different types of symptoms:

Example:
- *Vibration*
- *Interference*
- *Attitude*

Root cause Identification

17 different types of root-causes:

Example:
- *Hardware issue*
- *Tuning Issue*
- *Calibration Issue*

Symptom and root cause identification

Vibration-Accel	Interference	Attitude	GPS
Vibration	Interference	Desired Roll	latitude
Raw acceleration	interfare	attitude divergence	satellite
Raw accelerometer	interfaring	toilet bowling	longitude
VIBE	coupling	Excessive yaw	Lat
IMU	interfered	YAW drift	HDop
AccZ	throttle	angle of the scroll	NSats
AccX	magnetic field	wobbling	GPS.HDop
AccY	thrust	DesPitch	GPS.Alt
IMU.AccZ	MagX	violent turn	RelAlt
VibeX	MagY	DesYaw	SPD
VibeY	MagZ	ATT.DesPitch	GPS.Lat
VibeZ	MAG	ATT.Roll	Lng
vehicle_acceleration	MAG2	ErrYaw	GCrs
vehicle_imu	CTUN.ThR	ATT.ErrYaw	GPS.NSats
sensor_accel	CTUN.ThO	vehicle_angular_velocity	vehicle_gps_position
sensor_accel.x	actuator_controls[3]	vehicle_attitude	vehicle_global_position
sensor_accel.y	vehicle_magnetomete	vehicle_angular_acceleration	vehicle_gps_position.lat
sensor_combined	sensor_mag	vehicle_attitude_setpoint	vehicle_gps_position.lon

List of query terms

Anomaly Diagnosis

Symptoms

Vibe GPS EKF

Root Cause

Hardware Issue Tuning Issue

Root Cause

The high-level problem that is causing the anomalies in the data attribute(s).

Anomaly Diagnosis

Post	Vibration	Interference	Attitude	Power	EKF	... ...	Hardware	Isolation	Wiring	Weather	Sensor
	Symptoms						Root causes				
1	1	0	0	0	0	... ...	0	1	0	1	0
2	0	1	0	0	0	... ...	0	0	1	0	0
⋮	⋮	⋮	⋮	⋮	⋮	... ...	⋮	⋮	⋮	⋮	⋮
2763	0	0	0	0	0	... ...	0	0	0	0	0

Mined data from forum texts related **to co-occurring symptoms and root causes**

ARM

Rule: $X \Rightarrow Y$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

Applied Association Rule Mining

Association Rules

```
Rule: {'Power', 'GPS', 'Attitude'} -> {'Power issue'}
Confidence:  0.75
Lift:  3.376415094339623
=================================================================
Rule: {'Power', 'Attitude'} -> {'Motor', 'Hardware'}
Confidence:  0.225
Lift:  3.3977848101265824
=================================================================
Rule: {'Compass', 'Vibration', 'Tuning'} -> {'Calibration'}
Confidence:  0.5882352941176471
Lift:  3.1328781512605044
=================================================================
Rule: {'Vibration', 'Interference', 'Calibration'} -> {'Compass'}
Confidence:  0.875
Lift:  3.9391509433962266
=================================================================
```

Association rules that can recommend root causes given the detected symptoms

Anomaly Diagnosis

Symptoms

Vibe | GPS | EKF

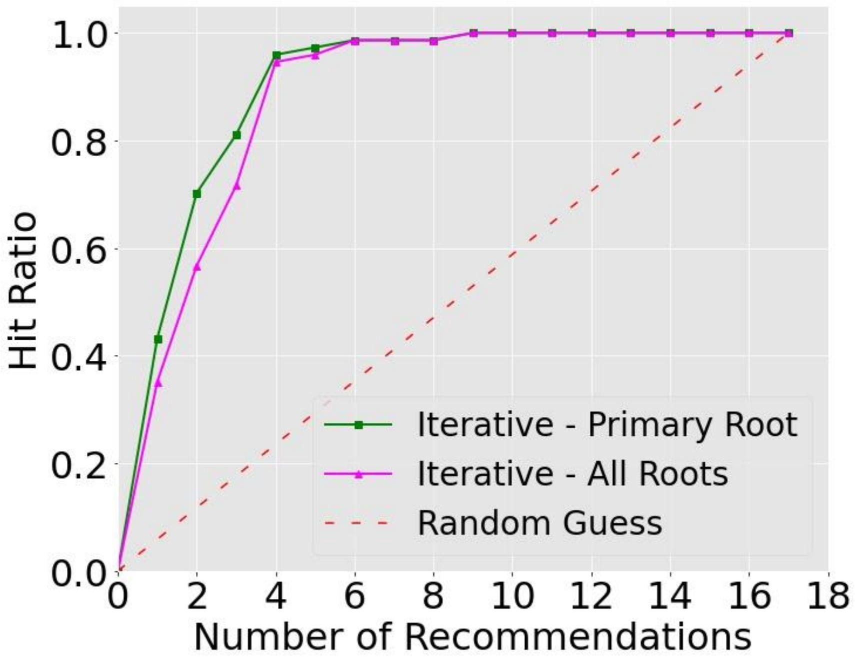
Root Cause

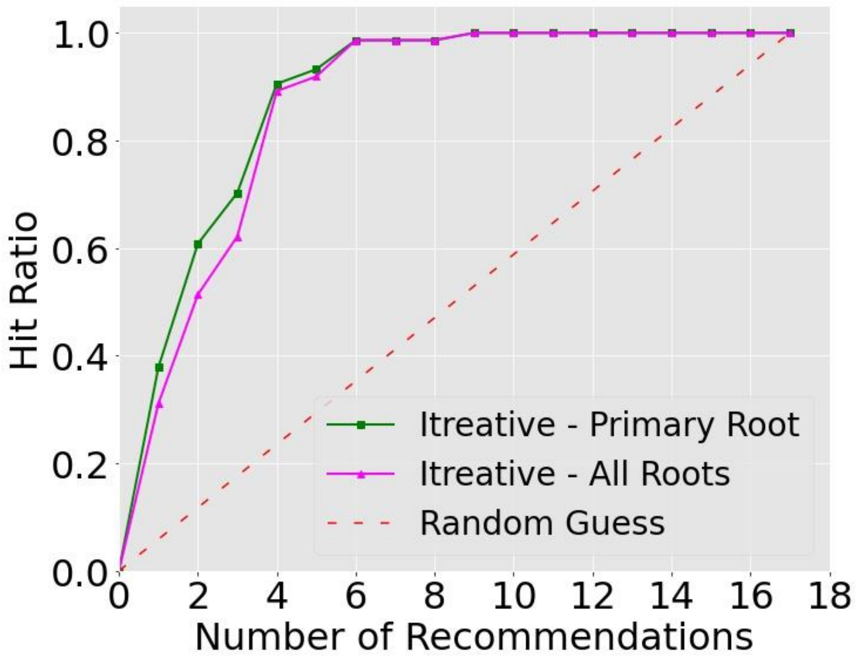
Hardware Issue | Tuning Issue

Root Cause

The high-level problem that is causing the anomalies in the data attribute(s).

Anomaly Diagnosis



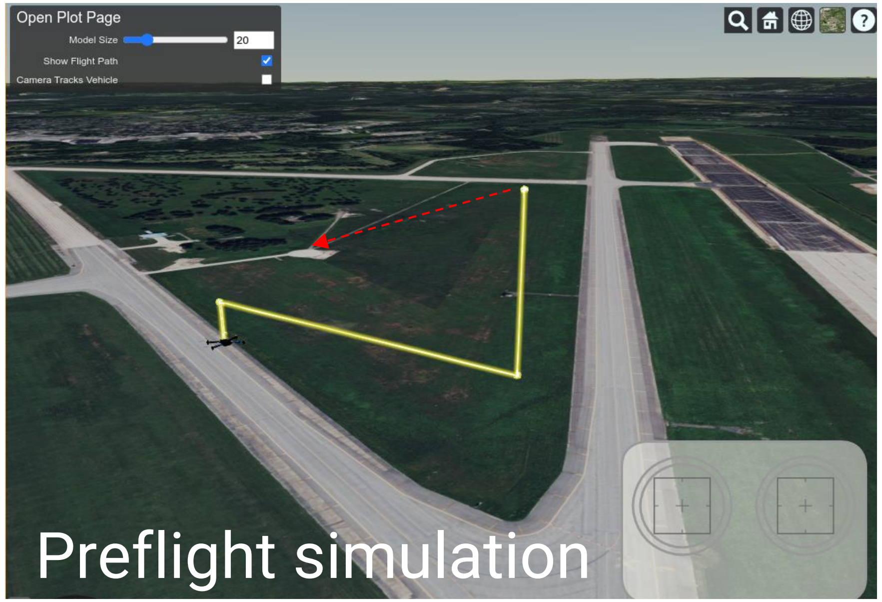


Case 1
Symptoms generated using both **problem description** and **anomaly detection** on the flight log

Case 2
Symptoms generated using **anomaly detection** on the flight log

What went wrong?

1



2

3

Post-mission, hovered for 20+ minutes for endurance test. Crashed in final minutes of flight!

The cause of the crash was not obvious at all. Engineers from our team, Griffiss airbase, and NASA deeply analyzed flight logs.

Flight log:
https://tinyurl.com/TEAL-Crash

- Cruise Altitude: 100 ft (30.4 m)
- Distance: 500 meters
- Max Alt: 129.41 meters

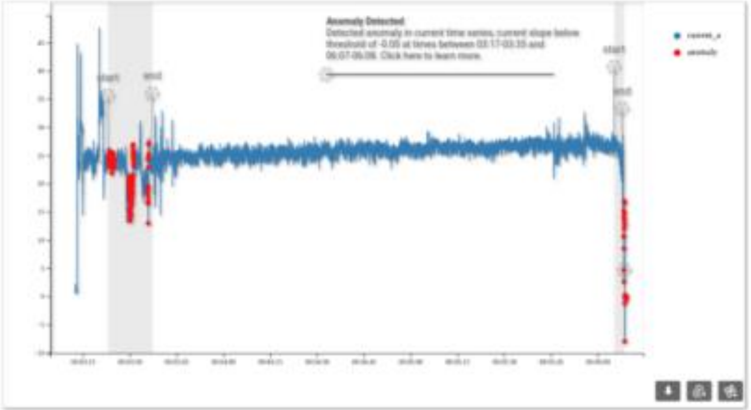
What went wrong?

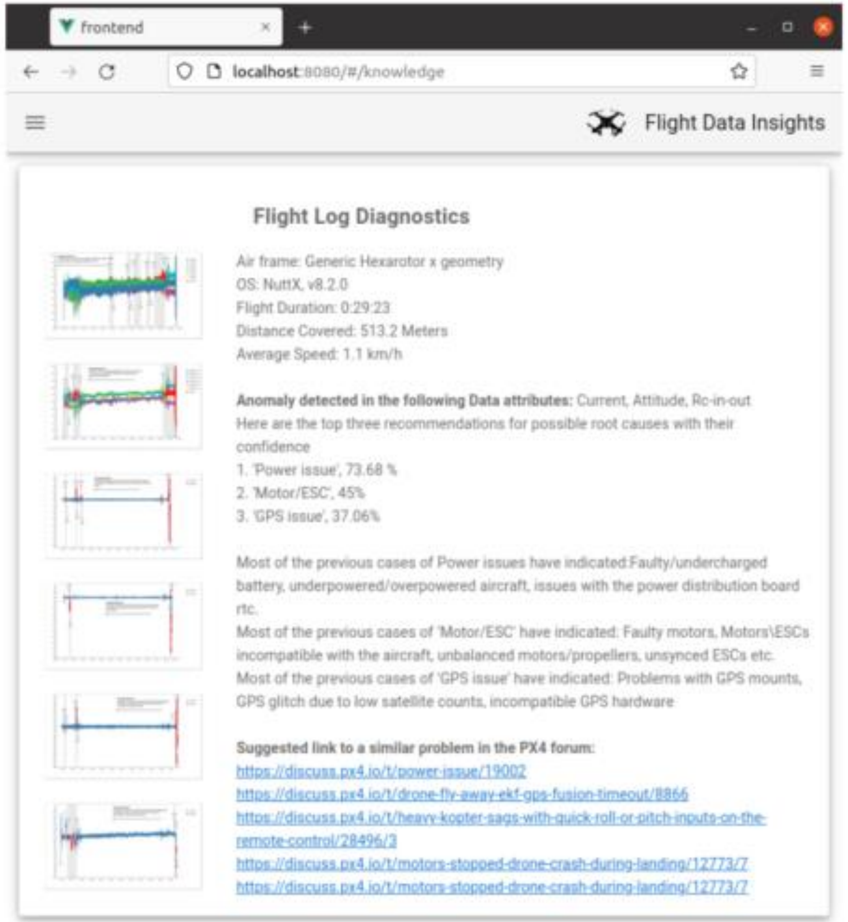
Anomalies Detected:
- RC-in-out
- Current
- Attitude

Top 3 recommendations from the ARM Model:

- Power (73.68%)
- Motor/ESC (45%)
- GPS Issue (37.06%)

(a) Anomalies were detected because the average outputs to a group of motors diverged excessively from another group by over 200 PWM.

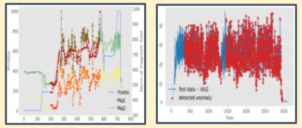




Data Collection and Community Support

Longitudinal Data Collection

Time series sensor data



Weather Data

Battery Info

Flight Plan

GCS Error Messages

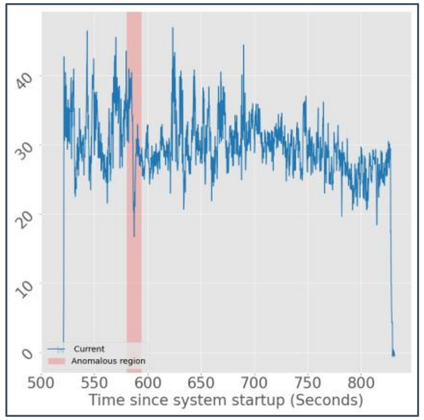
Post flight analysis

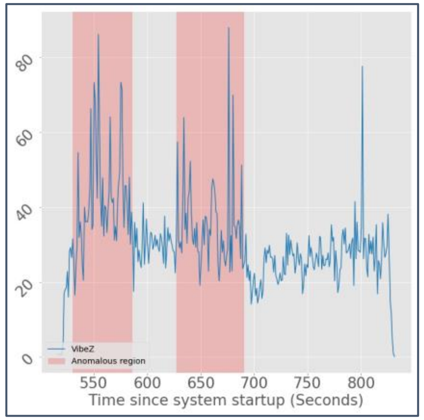
Additional Info

Islam et al., "Towards an Annotated All-Weather Dataset of Flight Logs for Small Uncrewed Aerial Systems" AIAA AVIATION 2023 Forum, June 2023

Annotating Anomalies

Anomaly ID	A00001	A00002	A00003
Flight-ID	F0012	F00001	F00002
Anomaly Tag	LOSS-OF-SIGNAL	ACCEL-CLIPPING	HIGH-VIBRATION
Description	Drone transitioned to HOVER state on failure to detect heart-beat from the GCS > 20 seconds. Heartbeat was restored & mission was completed.	An error message was raised stating "Accel 0 clipping, not safe to fly!" Upon landing we detected that the cap had opened creating significant drag.	High vibration was observed in the flight logs. Upon landing we detected that the cap had opened creating significant drag
Start Time	518	578	530
End Time	518	578	680
Observability	Observed during flight via BEEP to redundant Radio Controller, Flight logs.	During flight via error message, Flight Logs.	Flight logs only
Outcome	Exception case handled correctly during flight	Significant impairment with successful RTL	Significant impairment with successful RTL
Time-series	Timeline, vehicle_status.nav_state	Timeline, accel_clipping[0], accel_clipping[1], accel_clipping[2]	Timeline, var_accel[0], var_accel[1], var_accel[2]

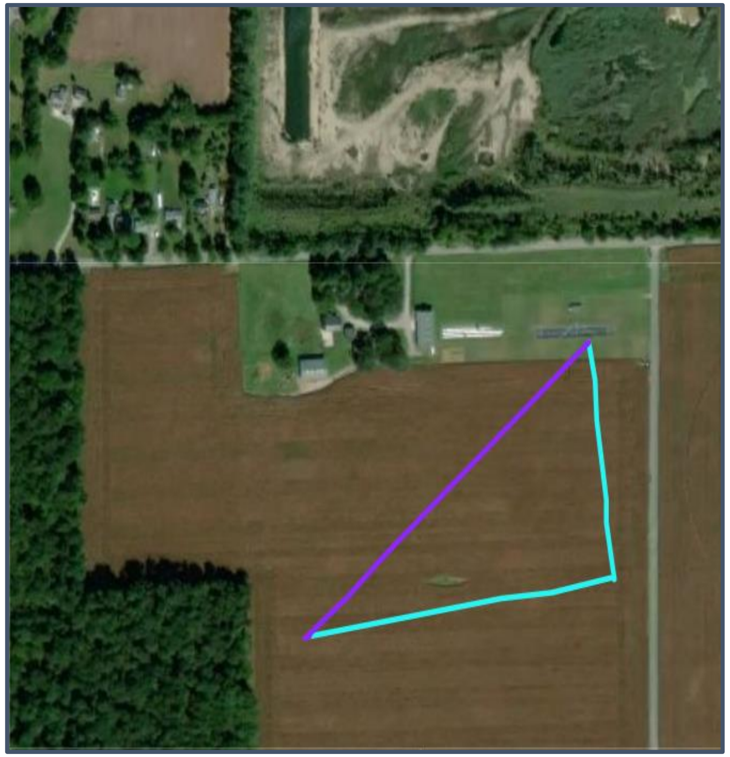




Islam et al., "Towards an Annotated All-Weather Dataset of Flight Logs for Small Uncrewed Aerial Systems" AIAA AVIATION 2023 Forum, June 2023

Collected Data - example of two flights

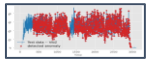
Planned flight
(simulation)



Flight 1

Flight 2

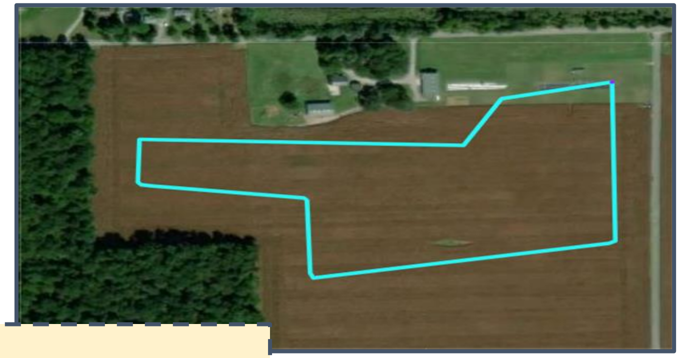
Collected Data - example of two flights

Information Type	Flight 1	Flight 2
Time-series Sensor Data 	All the sensor data extracted from the log file saved into separate CSV files	All the sensor data extracted from the log file saved into separate CSV files
Weather Information 	Weather model: GFS27 Wind: 8.26 knots NE Air temperature: 78F Dew point: N/A Relative Humidity: N/A Atm pressure (inHg): N/A	Weather model: GFS27 Wind: 6 knots N Air temperature: 66F Dew point: 48 Relative Humidity: 51% Atm pressure (inHg): 30.21
Battery Profile 	Battery ID: #10013 Specs: 16000 mah 6S 25C 22.2V Before Flight: Total Voltage: 25.1V C1: 4.17V C2: 4.21V C3: 4.18V C4: 4.17V C5: 4.15V C6: 4.21V After Flight: Total Voltage: 24.1V C1: 4.03V C2: 4.06V C3: 4.05V C4: 4.01V C5: 4.05V C6: 4.06V	Battery ID: #10017 Specs: 16000 mah 6S 25C 22.2V Before Flight: Total Voltage: 25.2V C1: 4.19V C2: 4.14V C3: 4.16V C4: 4.16V C5: 4.13V C6: 4.14V After Flight: Total Voltage: 23.8V C1: 3.94V C2: 3.92V C3: 3.94V C4: 3.94V C5: 3.90V C6: 3.92V

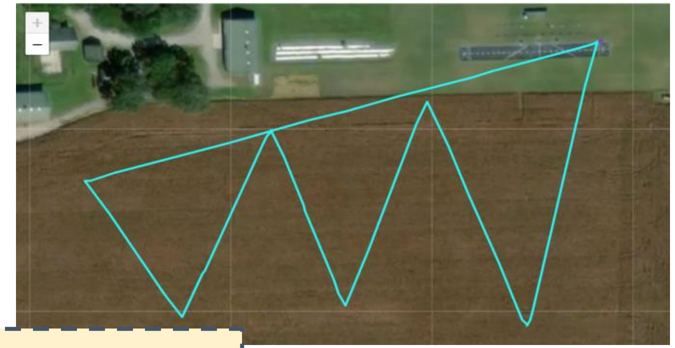
Collected Data - example of two flights

Information Type	Flight 1	Flight 2
Flight Path Information 	Waypoints traversed (lat, lon, alt(m)): 41.6066955094, -86.3555046667, 10 41.6045566645, -86.3554461571, 30 41.6040586892, -86.3595820504, 40 41.6066955094, -86.3555046667, 10	Waypoints traversed (lat, lon, alt(m)): 41.6066955094, -86.3555046667, 10 41.6045566645, -86.3554461571, 30 41.6040586892, -86.3595820504, 40 41.6087610934, -86.3602510006, 236 41.6066955094, -86.3555046667, 236
GCS Error Messages 	Avionics Power low: 4.60 Volt Accel 0 clipping, not safe to fly! Accel 2 clipping, not safe to fly! Land now, and check the vehicle setup. Clipping can lead to fly-aways.	Manual control lost Manual control regained after 0.8s Manual control lost Manual control regained after 0.2s
Post-flight Analysis Report 	Actuator outputs are fluctuating greatly with frequent minimum and maximum clippings indicating heavy and imbalanced payload. Current data shows that the sUAS was under-powered compared to its weight. This also caused high z-axis vibrations.	Because no GF_ACTION was set, the sUAS transitioned from OnBoard to stabilized mode. However, the throttle was slightly above neutral. Our current finding is that the throttle position caused the increase in altitude, and the sUAS' momentum plus the southerly wind caused it to head North.

Longitudinal Data Collection - Flight Routes



Polygon



Zigzag

Circle

North-South route

East-West route

Used sequentially to analyze the effects of wind direction

Islam et al., "Towards an Annotated All-Weather Dataset of Flight Logs for Small Uncrewed Aerial Systems" AIAA AVIATION 2023 Forum, June 2023

Acknowledgments

Thanks to all my collaborators


















Publications

ADAM: Adaptive Monitoring of Runtime Anomalies in Small Uncrewed Aerial Systems
Md Nafee Al Islam and others *(SEAMS'24)*

RESAM: Requirements Elicitation and Specification for Deep-Learning Anomaly Models with Applications to UAV Flight Controllers
Md Nafee Al Islam and others *(RE'22)*

Configuring mission-specific behavior in a product line of collaborating Small Unmanned Aerial Systems
Md Nafee Al Islam and others *(JSS'23)*

Towards an Annotated All-Weather Dataset of Flight Logs for Small Uncrewed Aerial System
Md Nafee Al Islam and others *(AIAA'23)*

Diagnosing and Explaining Flight Anomalies in small Unmanned Aerial Systems
Md Nafee Al Islam and others *(Work Completed)*

Requirements-driven configuration of emergency response missions with small aerial vehicles
J. Huang, A. Agrawal, Md Nafee Al Islam and others *(SPLC'20)*

Towards Real-Time Safety Analysis of Small Unmanned Aerial Systems in the National Airspace
J. Huang, N. Chawla, M. Cohen, Md Nafee Al Islam and others *(AIAA'22)*

RESAM: Requirements Elicitation and Specification for Deep-Learning Anomaly Models with Applications to UAV Flight Controllers
Md Nafee Al Islam and others *(RE'22)*

Detecting Anomalies in Small Unmanned Aerial Systems via Graphical Normalizing Flows
Yihong Ma, Md Nafee Al Islam and others *(IEEE Intel. Sys. '23)*

Hazard Analysis for Human-on-the-Loop Interactions in sUAS systems
M. Vierhauser, Md Nafee Al Islam and others *(FSE'21)*

Salil Purandare, Urjoshi Sinha, Md Nafee Al Islam, "Self-Adaptive Mechanisms for Misconfigurations in Small Uncrewed Aerial Systems
S. Purandare, U. Sinha, Md Nafee Al Islam and others *(SEAMS'23)*

Detection and Diagnosis of Flight Anomalies in Small Unmanned Aerial Systems

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12th November 2024