

Anomaly Mining and Visualization of Autonomous Aerial Vehicles

by

Jose Rosario Elenes Cazares

A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Science

Approved November 2022 by the
Graduate Supervisory Committee:

Chris Bryan, Chair
Javier Gonzales Sanchez
Ayan Bannerjee

ARIZONA STATE UNIVERSITY

December 2022

ABSTRACT

The drone industry is worth nearly 50 billion dollars in the public sector, and drone flight anomalies can cost up to 12 million dollars per drone. The project's objective is to explore various machine-learning techniques to identify anomalies in drone flight and express these anomalies effectively by creating relevant visualizations. The research goal is to solve the problem of finding anomalies inside drones to determine severity levels. The solution was visualization and statistical models, and the contribution was visualizations, patterns, models, and the interface.

TABLE OF CONTENTS

	Page
LIST OF TABLES	v
LIST OF FIGURES	vi
CHAPTER	
1 INTRODUCTION	1
1.1 What Is a Drone?	1
1.2 What Are Drones Used For?	2
1.3 What Goes Wrong with Drone Flights?	3
1.4 Motivation	3
1.4.1 Why Is Drone Flight Analysis Important?	4
1.4.2 Why Is Visualization a Viable Approach?	5
1.5 Terminology	5
1.5.1 Normal Flights	6
1.5.2 Anomalies (Conflicts)	6
1.5.2.1 Concentration Waves	7
1.5.2.2 Electromagnetic Waves	8
1.5.2.3 Transients	9
1.5.2.4 Phase Changes	11
2 BACKGROUND	13
2.1 Current Industry / Research Standards	13

CHAPTER	Page
2.2 Problems with Drone Analysis	17
3 DESIGN REQUIREMENTS AND METHODOLOGY	18
3.1 Design Requirements	18
3.1.1 Flexible and Interactive Data Retrieval	18
3.1.1 Temporal Analysis and Anomaly Discovery	18
3.1.1 Multiple Perspectives	19
3.1.1 Data Wrangling	19
3.1.2 Drone Tracker	22
3.2 Methodology	23
3.2.1 Backend Models	24
4 SYSTEM COMPONENTS	35
4.1 Components	35
4.1.1 Backend	35
4.1.2 Frontend	35
4.2 Interface description	35
4.2.1 Idiom Abstraction	36
4.2.2 Map	36
4.2.3 Attribute Charts	37
4.2.4 Control Panel for Flight Selection	37

CHAPTER	Page
4.2.5 Time Slider	38
4.2.6 T-sne	38
4.2.7 Radar	39
4.2.8 Heatmap	40
4.2.9 Flight Anomaly Isolation	41
5 ANALYSIS AND CASE STUDIES	42
5.1 Analysis	42
5.1.1 Minmax Scaler	43
5.1.2 Standard Scaler	44
5.1.3 Association Mining	44
5.2 Case Studies	45
5.2.1 Case Study 1 - Flight 2	45
5.2.2 Case Study 2 - Flight 11	48
6 RESULTS AND IMPLICATIONS	55
6.1 Limitations	55
6.2 Challenges	56
6.2 Conclusion	57
REFERENCES	59

LIST OF TABLES

Table		Page
3.3	Attributes Used	19

LIST OF FIGURES

Figure	Page
1.1 Image of a Drone	1
1.2 Uses of Drones	2
1.3 Crashed Drone	4
1.4 Drone Watering Plants	6
1.5 The Electromagnetic Spectrum	8
1.6 Transients.....	9
2.1 Ardupilot Interface	13
2.2 Ardupilot Plots	14
2.3 Flight Movement with Graphs	15
2.4 Topological Plots of Anomalies	15
2.5 A Heatmap of a Research Study	16
3.1 Mavlogdump Attribute Extraction	17
3.2 Six Sigma Defects per Million	18
3.4 Steps Followed Using the Interface	20
3.5 A survey of Literatures in Anomaly Detection	22
3.6 Lstm Predicting Temperature and Pressure	23
3.7 Faster Matrix Multiplication Algorithms	25
3.8 Anomalies Converted to Transactions	27

Figure		Page
3.9	Association Models	27
3.10	Data Distributions for Process Average	27
3.11	T-sne Approach Example	28
3.12	Dynamic Time Warping Example	29
3.13	Dynamic Time Warping Uses in Deep Neural Networks	30
4.1	Image of Interface	32
4.2	Map as an Example for Interface Walkthrough	33
4.3	T-sne as an Example for Interface Walkthrough	35
4.4	Radar as an Example for Interface Walkthrough	35
4.5	Heatmap as an Example for Interface Walkthrough	36
4.6	Dynamic Time Warping as an Example for Interface Walkthrough	36
5.1	Lstm Model Training Accuracy for Minmax Scaler	38
5.2	Lstm Model Training Accuracy for Standard Scaler	39
5.3	Association Rules Above 6 Standard Deviations for Case Study 1	40
5.4	T-sne and Gps Map for Case Study 1	41
5.5	Dynamic Time Warping Similarity for Case Study 1	42
5.6	Association Rules Above 6 Standard Deviations for Case Study 2	43
5.7	T-sne and Gps Map for Case Study 2	44
5.8	Association Rules Below 6 Standard Deviations for Case Study 2	45
5.9	Heatmap Below 6 Standard Deviations for Case Study 2	48

Figure		Page
5.10	T-sne Vibrations and Throttle Input for Case Study 2	49
5.11	T-sne Displaying Throttle Output and Roll for Case Study 2	49
5.12	T-sne and Similarity with Flags of Battery for Case Study 2	50
5.13	Similarity and Throttle Input and Output Flags for Case Study 2	50
5.14	Flight 11 Vibrations and Roll Similarity for Case Study 2	51

CHAPTER 1

INTRODUCTION

1.1 WHAT IS A DRONE?



Figure 1.1: Drones are expensive and have many shapes and sizes (Zachary Kallenborn, 2021).

Computer integration into engineering designs, such as aerial vehicles, helps to automate an unmanned aerial vehicle. Commonly known as a drone, an aircraft without any human pilot, crew, or passengers on board, it is a flying computer (WIKIPEDIA, 2022). Autonomous aerial vehicles in the past have used heuristics, supervised machine learning, and recently unsupervised machine learning (Kyung Ho Park et al, 2021). Until

now, we have assumed that time is continuous, and for the computer, time is not continuous; it passes in discrete intervals. In other words, time can take on any value, and this is generally true of Non-linear physical systems involving components such as capacitors, masses, and thermal resistances (Henning D., 2020). Understanding the ramifications of the inherently discrete nature of time with embedded computers is essential in analyzing drone performance.

1.2 WHAT ARE DRONES USED FOR?



Figure 1.2: Drone operation commissioned by international governments, (a) Payload delivery. (b) Intelligence gathering. (c) Nuisance activity. (d) Cyber and random attacks (Aquilina, R., 2022) (Ally Foster, 2019) (Pilot Institute, 2020) (Anna Ahronheim, 2022) (Verdict media limited, 2022).

Unmanned aerial vehicle applications include agriculture. The drone research data for this paper is from agriculture, and the drones used for data capture specialize in microclimates for agriculture fields. A microclimate is a distinct, localized climate of a small-scale area. Drone implementations include payload delivery, intelligence gathering, nuisance activity, and random cyber attacks.

1.3 WHAT GOES WRONG WITH DRONE FLIGHTS?

Drones can crash and cause unwanted events, such as flying in the wrong direction because of a damaged propeller and watering at the wrong place. The worst scenario when a drone crashes is shooting at civilians, and it cannot correct its physical errors, such as damaged sensors.

1.4 MOTIVATION

Complex coded rules by engineers and their problems are complicated when inventors need help comprehending their design mistakes. It is exciting to extract problems from machines without understanding how they work.

1.4.1 WHY IS DRONE FLIGHT ANALYSIS IMPORTANT?



Figure 1.3: Drones fail, and when users interact with drones, they are destroyed permanently (Craig Whitlock, 2014).

Drone flights generate high-volume data, and it is difficult to analyze and understand anomalies caused by inconspicuous drone flight features in complex data. We have data that can help us identify if the drone is flying incorrectly and why it may be doing so. We are not concerned with exactly what the drone is recording as measurements. For instance, in our data, the drone could fly to the wrong portion of the field and take incorrect measures. It is essential because of worst-case scenarios. Our attributes identify whether the drone is flying correctly. Drone anomalies can destroy equipment, increase costs, and cause loss or injury to human life. The ability to detect anomalies helps to control yields, secure engineering technology, and advance scientific research.

1.4.2 WHY IS VISUALIZATION A VIABLE APPROACH?

Utilizing computing resources that resemble human thinking has improved since the development of the first computers, and visualizing Information in a human-understandable format through Visualization extends human cognition. Algorithms output is not human-understandable. Effective data visualization allows us to make timely predictions and prevent anomalies or crashes. Visualization helps reduce operator overhead when analyzing drone flights and enables multi-level analysis using different models to provide holistic analysis. Artificial Intelligence can experience similar logical problems as natural intelligence due to the learning and training requirements of neural networks. Synthetic and Natural Intelligence have similar mathematical properties; humans have neural networks, and so does AI. Projecting data incorrectly without considering anomalies causes spatial information loss and restricts human perception.

1.5 TERMINOLOGY

Anomaly definitions and relevant terms are in this section.

1.5.1 NORMAL FLIGHTS



Figure 1.4: Drone watering plants are essential to replace human labor (PanosCs, 2022).

Ideally, automated tasks are performed flawlessly, with no contamination of the environment. A routine flight is where failure does not occur, or negligence is marginal to where there is no destruction of life and property.

1.5.2 ANOMALIES (CONFLICTS)

Transients are examples of anomalies seen in concentration waves and electromagnetic waves. For example, drones can have electrostatic charge build over time, causing short circuits and sensor activation. Concentration and Electromagnetic wave sensors capture time series data, and our drone flight data follows this structure.

1.5.2.1 CONCENTRATION WAVES

Oscillations

Periodic movements of particles have the potential to initiate waves but have yet to convert to waves. Oscillations can transition into actual problems by deviating from their usual. For example, accumulated charges in the structures of drones can cause transients.

Mechanical waves

A mechanical system can transfer energy (and momentum) from one place to another in two ways (University of Germany, 2022). The simplest is to send an object — for example, a bullet — carrying mass, momentum, and energy from the "source" to the "receiver" (University of Germany, 2022). A more complex method is called wave motion (University of Germany, 2022). The system of these particles (gas, liquid, or solid) is called the medium. Mechanical waves occur by the interaction between neighboring particles in the medium. One characterizes this transfer by three quantities: its direction, its speed (v), and its rate of energy transfer, measured by its intensity (I). Concorde supersonic airplane, crashed when debris was thrown against the wing structure and ruptured fuel tank 5 (LOGEMENT, M. D. L. D. T. E. D., 2001). A major fire, fuelled by the leak, broke out under the left wing (LOGEMENT, M. D. L. D. T. E. D., 2001.). Problems appeared shortly afterward on engine two and for a brief period on engine 1 (LOGEMENT, M. D. L. D. T. E. D., 2001.). The aircraft took off but was not able to

climb or accelerate (LOGEMENT, M. D. L. D. T. E. D., 2001).

1.5.2.2 ELECTROMAGNETIC WAVES

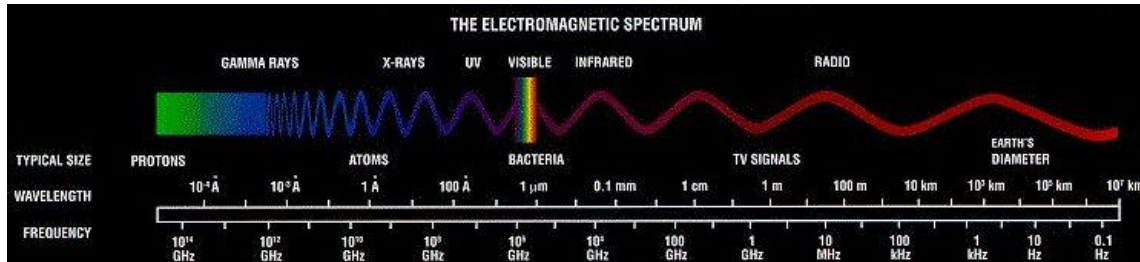


Figure 1.5: The Electromagnetic spectrum in frequency, hertz, or electron volts. Short wavelengths, such as gamma radiation, have tremendous energy, while radio wavelength is longer with less electromagnetic radiation. (David J Bromlay, 2022).

Standing waves

These standing wave modes arise from the combination of reflection and interference such that the reflected waves interfere constructively with the incident waves. An essential part of the condition for constructive interference is that the waves change phase upon reflection from a fixed end.

Traveling waves

A *wave pulse* is a disturbance that moves through a medium (The University of Tennessee, 2022). A *periodic wave* is a frequent disturbance that moves through a medium, and the medium itself goes nowhere (The University of Tennessee, 2022). Energy transfer throughout the medium occurs without transporting any matter. The individual atoms and molecules in the medium oscillate about their equilibrium position,

but their average status does not change. As they interact with their neighbors, they transfer some of their energy to them. The neighboring atoms, in turn, transfer this energy to their neighbors down the line.

1.5.2.3 TRANSIENTS

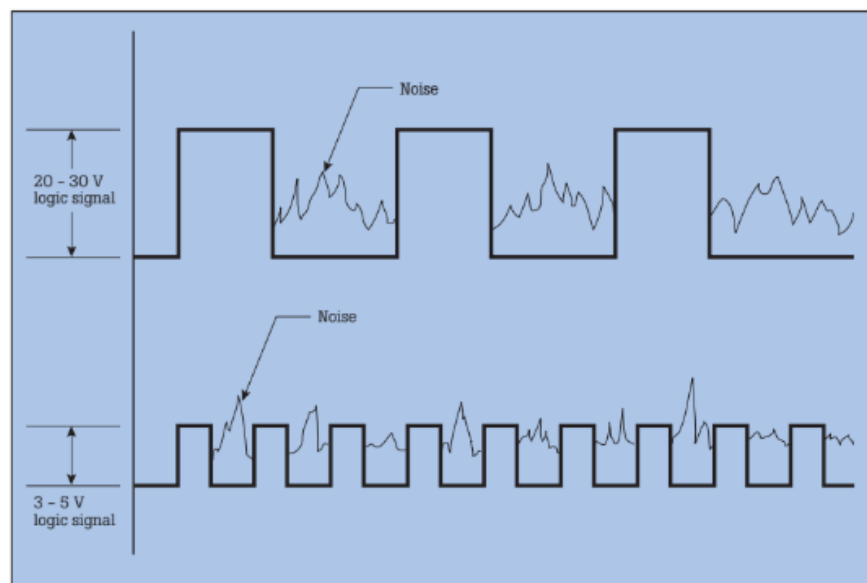


Figure 1.6: Circuits represent transfer functions that symbolize current, voltage, and other variables. Transients disrupt transfer functions. Electrical transients, such as noise in transfer functions in electronic circuits, are shown above (Fluke Corporation, 2004).

Transients are unavoidable and occur by the fast switching of relatively high currents. Removing a solenoid voltage tester from a high-energy circuit can create a spike of thousands of volts (Fluke Corporation, 2004). A capacitor, on the other hand, creates a momentary short circuit (Fluke Corporation, 2004). For example, an inductive load like a motor will create a kickback spike when turned off (Fluke Corporation, 2004). Not all

transients are the same, but as a general statement, load switching causes transients (Fluke Corporation, 2004).

Rapid acceleration

Accelerated vibration in a linear-duct configuration is best suited for fusion power generation on aircraft or main battle tanks. The fusion fuel is introduced into the plasma core through the counter-spinning conical structures and injected through orifices in the dynamic fusor heads. Controlled motion of electrically charged matter through accelerated vibration and accelerated spin subjected to smooth yet rapid acceleration transients to generate extremely high-energy/high-intensity EM radiation (fields of high-energy photons) confines the plasma (S. C. Pais, 2019). This process significantly compresses it to produce a high power density plasma burn, leading to ignition—the voltage rebounds after the collapse of the applied voltage.

Internal transients

Transients can constantly occur rather than through short impulses, such as continuous current leakage over time from one area to another in a circuit. Internal flaws and wear contribute to these problems (Do Y et al, 2005).

Externally generated transients

Charge transfer is not confined to internal forces since wave properties can penetrate different materials' depths due to electron clouds. Inert materials are essentially a fabric of atoms where waves can leak charge, mainly due to the wave-particle duality.

The real world exhibits steady and non-steady state dynamics and will statistically contribute to transients in inert materials.

1.5.2.4 PHASE CHANGES

There are many phase changes beyond the ones listed in this section and are only examples.

Solids

Atoms vibrate in place and do not slide past one another—for example, metals such as iron at room temperature. Solids are hard and hold their lattice hold the position of atoms in place.

Liquids

Atoms can vibrate, slide past one another, and move in a medium such as water. Liquids do not hold their shape, their atoms move all over, and their lattice structure does not hold atoms in place.

Gasses

An atom's radius from other atoms is a significant distance, such as oxygen and nitrogen. A significant distance separates the atoms in gasses, and human lungs can inhale gasses.

Plasma

Gasses are ionized and then transformed into plasma. Lighting is an example of plasma where atoms are ionized, seen in thunder.

Time crystal

Plasma becomes a crystal due to plasma electrons and the flow of cold ions (A. M. Ignatov, 2021). A typical crystal's structure repeats in space, while a time crystal repeats in time (Taylor Kubota, 2021).

CHAPTER 2

BACKGROUND

2.1 CURRENT INDUSTRY / RESEARCH STANDARDS

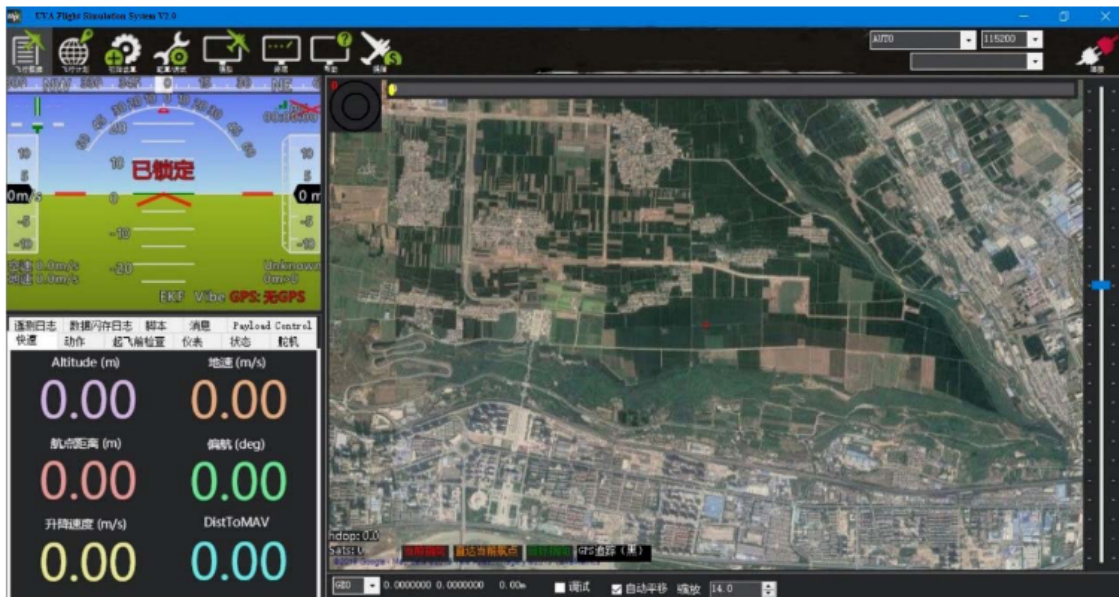


Figure 2.1: The main interface of ArduPilot. The interface is what the user sees when opening ArduPilot software (Mission Planner, 2022).

This chapter describes some common examples of visualizations of drone data used by other studies. Ardupilot captured data for this project, and ArduPilot software exclusively plots data with no algorithmic integration. ArduPilot visualizes GPS and satellite real-world data from sensors.

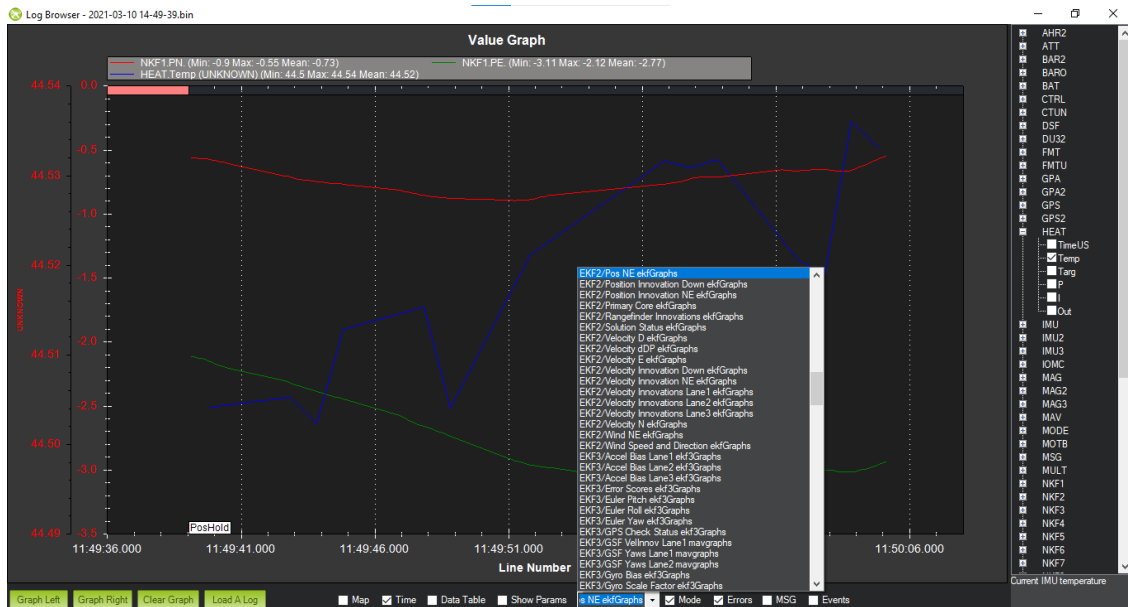


Figure 2.2: ArduPilot is capable of data capture and plots. However, it is not able to perform algorithmic calculations of data. ArduPilot allows for the selection of attributes to be plotted or a predefined combination of plots to be generated. Console access to generate plots is available (Mission Planner, 2022).

The platform where this study data is based is limited to creating plots of the variables and comparing them side by side and console manipulations of these plots. Algorithmic models are not embedded into Ardupilot because it specializes in data capture. Multiple graphs are displayed; this technique includes having several attributes of time series data in the same chart. Line plots alone cannot be used to find rules of electrical anomalies due to the inherent complexity and high-dimensionality of drone data.

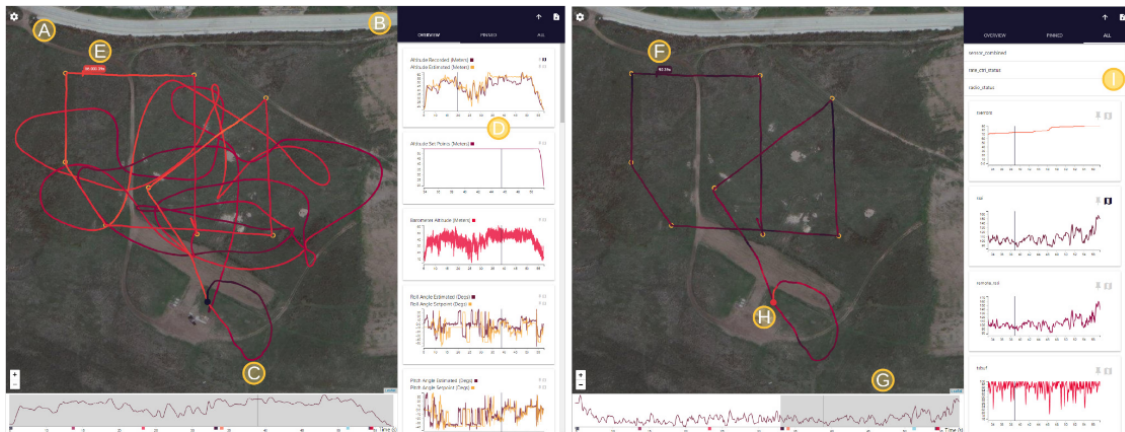


Figure 2.3: The user can compare the map and line charts, but it is the manual matching of which line chart to use from the list (David Saffo et al, 2020).

Visualization is helpful in understanding errors or identifying patterns when paired with algorithmic analysis. Scientists can map and compare line charts in academic studies, but it is manual matching and not an automated process. Drones are visualized primarily by comparing attributes and overlapping them in the same plot.

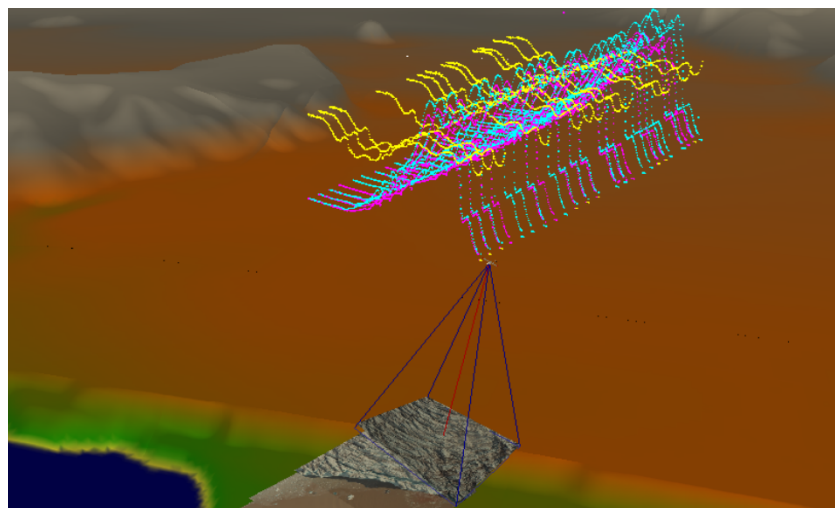


Figure 2.4: It gives the user an overview without many backend details. Drone topography research in 3D renders spectrometer data at the location where the sensors captured the data. The data is tilted and oriented according to the aircraft's yaw, pitch, and roll (Stødle, D., 2013).

GPS graphs with 2D density planes contribute to a stronger correlation in spatially identifying anomalies. Adding regions to maps with contrasting intensities can help to visualize the location of the errors that occurred. Heatmaps condense visual anomalies in time series, and comparing the flags is a tedious manual mapping.

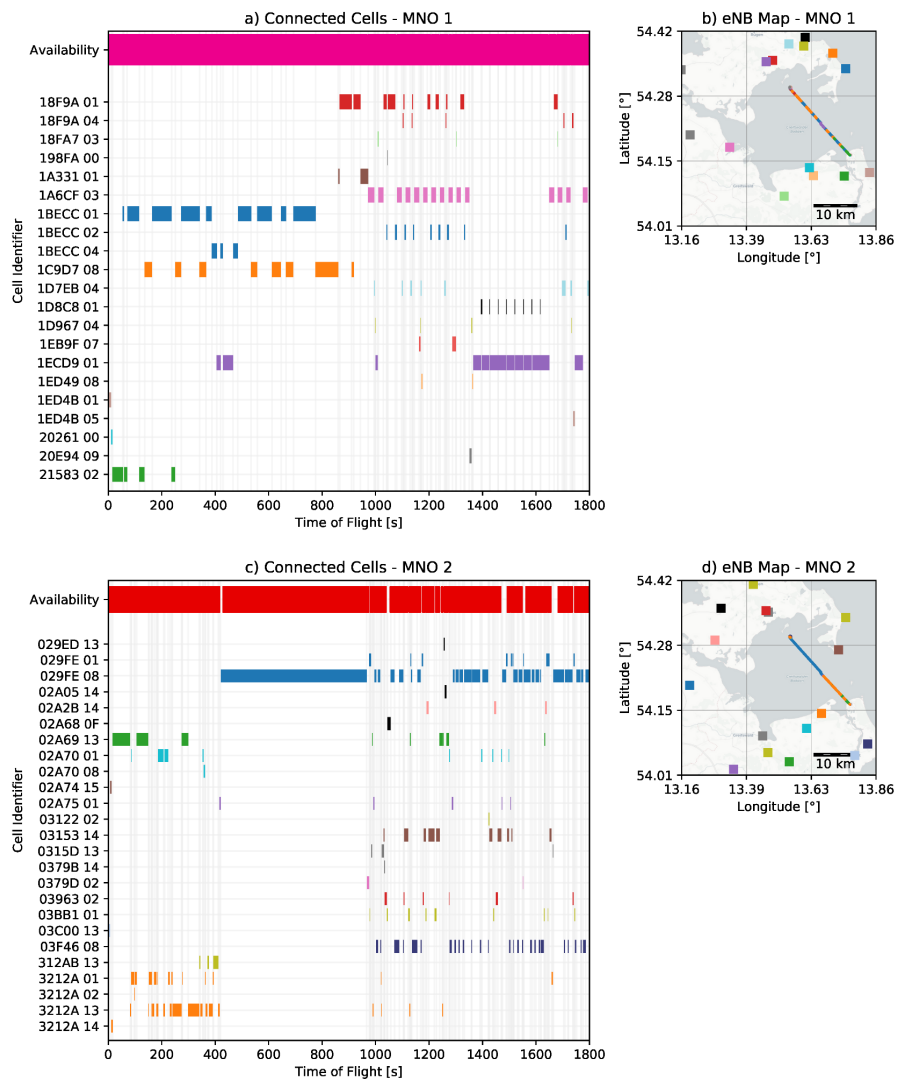


Figure 2.5: Comparing flagged anomalies involves tedious manual mapping between the map view and time-series glyphs. (Güldenring, J. et al, 2020).

2.2 PROBLEMS WITH DRONE ANALYSIS

The research emphasized anomalous data discovery, and the data did not have labels for defective drone flights. There needed to be more data because of problems with sensors needing to collect data properly and unknown factors. The time series data is complex and semi-structured in the format of *.bin or *.log.

CHAPTER 3

DESIGN REQUIREMENTS AND METHODOLOGY

3.1 DESIGN REQUIREMENTS

The design and methods and algorithms explanations are in this section.

3.1.1 FLEXIBLE AND INTERACTIVE DATA RETRIEVAL

The interface that the lab developed exhibits flexible and interactive data retrieval.

The user can select multiple flights, remove them or select one section at a time or all sections of the interface. The user can scroll through the graphs, set thresholds, and search for patterns by highlighting sections in graphs.

3.1.2 TEMPORAL ANALYSIS AND ANOMALY DISCOVERY

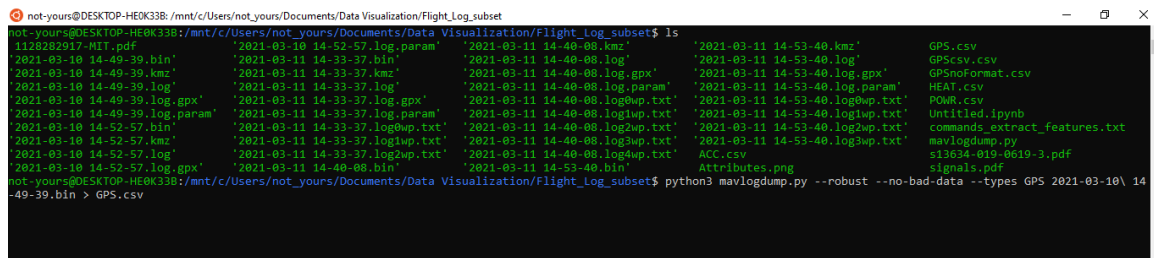
The interface supports temporal analysis of drone flights at the different granularity and anomaly discovery during drone flights. For example, highlighting a flight in the flight anomaly isolation section for an attribute sequence using the mouse and

positioning it at the selected pattern will return the top ten sequences. Also, the same graph will show problematic flags and order all flights according to similarity.

3.1.3 MULTIPLE PERSPECTIVES

The interface provides multiple perspectives for analyzing drone flights. Over six models uniquely represent problems with the data. These models incorporate visualization separate from the algorithms to augment perception.

3.1.4 DATA WRANGLING



```
not-yours@DESKTOP-HE0K33B: /mnt/c/Users/not_yours/Documents/Data Visualization/Flight_Log_subset$ ls
1128282917-MIT.pdf      '2021-03-10 14-52-57.log.param'  '2021-03-11 14-40-08.kmz'      '2021-03-11 14-53-40.kmz'      GPS.csv
'2021-03-10 14-49-39.bin'  '2021-03-11 14-33-37.bin'      '2021-03-11 14-40-08.log'      '2021-03-11 14-53-40.log'      GPS.csv
'2021-03-10 14-49-39.kmz'  '2021-03-11 14-33-37.kmz'      '2021-03-11 14-40-08.log.gpx'  '2021-03-11 14-53-40.log.gpx'  GPSnoformat.csv
'2021-03-10 14-49-39.log'  '2021-03-11 14-33-37.log'      '2021-03-11 14-40-08.log.param' '2021-03-11 14-53-40.log.param' HEAT.csv
'2021-03-10 14-49-39.log.gpx' '2021-03-11 14-33-37.log.gpx'  '2021-03-11 14-40-08.log0up.txt' '2021-03-11 14-53-40.log0up.txt' POWR.csv
'2021-03-10 14-49-39.log.param' '2021-03-11 14-33-37.log.param' '2021-03-11 14-40-08.log1up.txt' '2021-03-11 14-53-40.log1up.txt' Untitled.ipynb
'2021-03-10 14-52-57.bin'  '2021-03-11 14-33-37.log0up.txt' '2021-03-11 14-40-08.log2up.txt' '2021-03-11 14-53-40.log2up.txt' commands_extract_features.txt
'2021-03-10 14-52-57.kmz'  '2021-03-11 14-33-37.log1up.txt' '2021-03-11 14-40-08.log3up.txt' '2021-03-11 14-53-40.log3up.txt' mavlogdump.py
'2021-03-10 14-52-57.log'  '2021-03-11 14-33-37.log2up.txt' '2021-03-11 14-40-08.log4up.txt' '2021-03-11 14-53-40.log4up.txt' s13634-019-0619-3.pdf
'2021-03-10 14-52-57.log.gpx' '2021-03-11 14-40-08.bin'      '2021-03-11 14-53-40.bin'      Attributes.png                  signals.pdf
not-yours@DESKTOP-HE0K33B: /mnt/c/Users/not_yours/Documents/Data Visualization/Flight_Log_subset$ python3 mavlogdump.py --robust --no-bad-data --types GPS 2021-03-10\ 14
-49-39.bin > GPS.csv
```

Figure 3.1: MAVlogDUMP is used to generate CSV attributes files. The attribute files generate a complete list, such as All flight attributes CSV.

Mission Planner software ArduPilot captured data from drone sensors. The Information comprises structures in the *.bin and *.log format; measurements occur over time. The data includes numerical, categorical, and binary attributes. A script named MAVlogDUMP extracts all features from ArduPilot software as CSV with full columns

and rows. MAVlogDUMP and CSV transformed *.log files into a computer-readable form for algorithmic analysis.

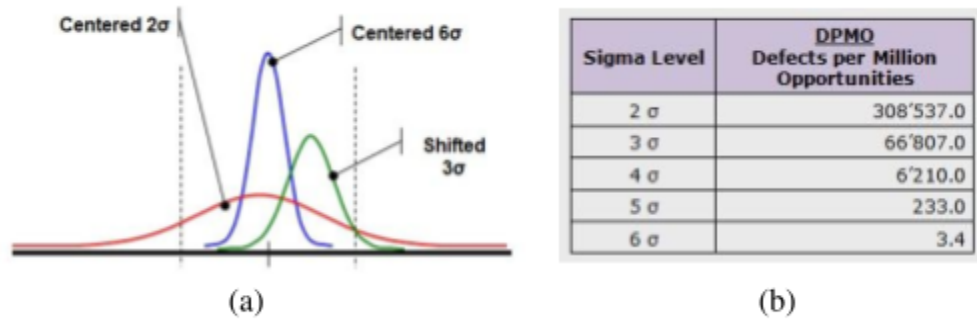


Figure 3.2: (a) Standard deviation and data shifting with respect to the mean. (b) Process defects per million opportunities and standard deviation (lean sigma corporation, 2022).

The output of this script is the CSV file for a particular attribute, and the features predicted were filtered for time series compatibility. A merging technique concatenates all points into one file, including removing null or missing parts.

Additionally, nan values are replaced with zeros to remove undefined values.

Standard deviation is a distance metric that helps filter signals similar to a band-pass filter. Six standard deviations threshold filter classifies unfiltered anomalous data.

Anomalous region classification occurs with the mean above and below the standard deviation and is user-defined. If thresholds are too low, anomalies will appear in great numbers, and if the points are high, warnings will not appear.

Features			
Number	Acronym	Name	Description
1	POWR	Power	Energy usage
2	HEAT	Heat	Heat distribution
3	ATT	Altitude	Canonical vehicle attitude
4	BARO	Barometer	Barometer data
5	BAT	Battery	Battery information
6	CTRL	Control	Attitude Control oscillation monitor diagnostics
7	CTUN	Control	Control Tuning information
8	GPA, GPA2	Accuracy	GPS accuracy information
9	GPS, GPS2	GPS	GPS information
10	IMU,IMU(2-3)	gyroscope	gyroscope information
11	MAG,MAG(2-3)	magnetic field	Magnetic field information
12	MOTB	Battery	Battery information
13	NKF(1-9)	Estimator	EKF2 estimator outputs
14	NKQ(1-2)	Quaternion	EKF2 quaternion defining the rotation from NED to XYZ (autopilot) axes
15	POS	position	Position information
16	PSC	position	Position information
17	RATE	attitude	Desired, achieved attitude rates
18	TERR	Terrain	Terrain database information

Table 3.3: Attributes used for time-series anomaly detection.

We used the CSV format since it is easy to manipulate data in a language with low complexity and for easy computation in python. The CSV file has all data attributes as columns, and data corresponding to the timestamps will be rows. The python script removes the flights which have missing features and null values. The python script concatenates all the flight data into a single consolidated file with the column "flight" with

the flight number. The apriori algorithm filtered anomalies second to the standard deviation and filtered the data twice. Statistical correlations with nan values will not display correctly, and nan values become zeros. The neural network training includes all-time series features, including the other models. Data deletion occurs when there are no time series patterns. A training set and testing evaluate performance. The trained model is saved and called by a python script for use in HTML to predict flights.

3.1.5 DRONE TRACKER

Imported and trained ML models are saved for external use and not coupled with the server to generate visualizations. One of the primary objectives of the model should be robustness and responsiveness. The training code is not required and increases code complexity.

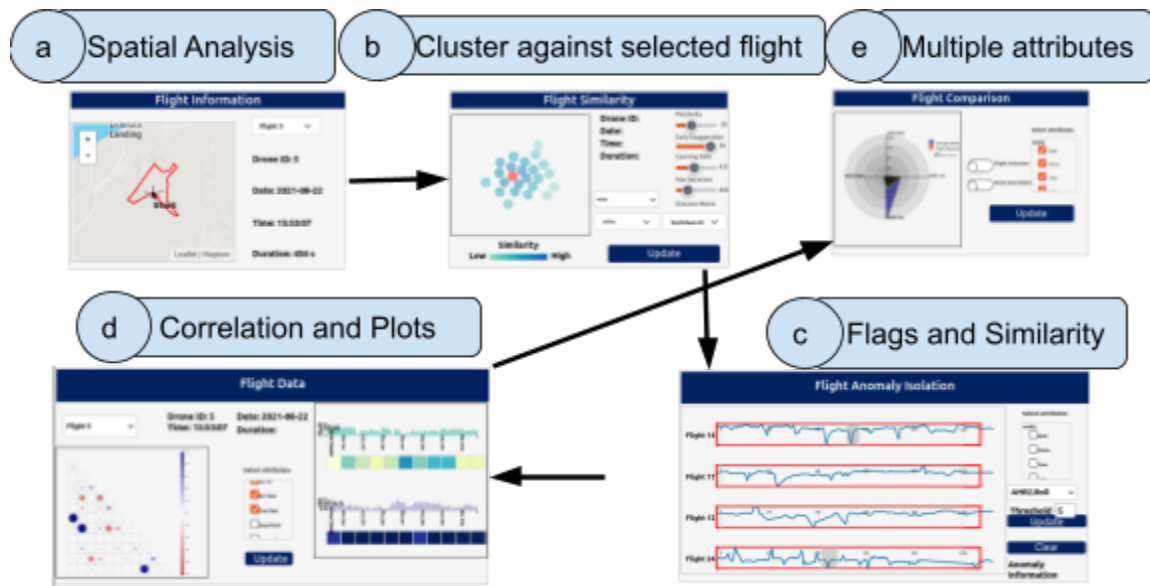


Figure 3.4: Walkthrough of the analysis pipeline.

The spatial analysis in Figure 3.4 (a) provides users with a top-down perspective, such as immediate feedback on movement. In clustering against selected flights in Figure 3.4 (b), selected flights are oriented to the cluster and compared to all other flights to see if they are in the border or outside the cluster. The flags and similarity section in Figure 3.4 (c) displays the flags per attributes selected, compares the selected flight to all other flights, and finds similarities based on the standard deviation entered. Also, in the correlation plots in Figure 3.4 (d), the user can plot the attributes, see the heatmap per time slice or graph the attributes using a correlation matrix as a heatmap. In the multiple attributes section in Figure 3.4 (e), a maximum of seven flight attributes display simultaneously to compare flights, but there can be fewer than seven selected.

3.2 METHODOLOGY

The main focus is supervised machine learning (ML) using an LSTM and unsupervised ML using association rule mining and clustering. Anomaly detection methods with current drone technology include online and offline training processes. Online training is when data comes in dynamically, and offline training is when data is in memory. Offline training is the topic in the research, and anomaly detection incorporated Multivariate Time Series.

3.2.1 BACKEND MODELS

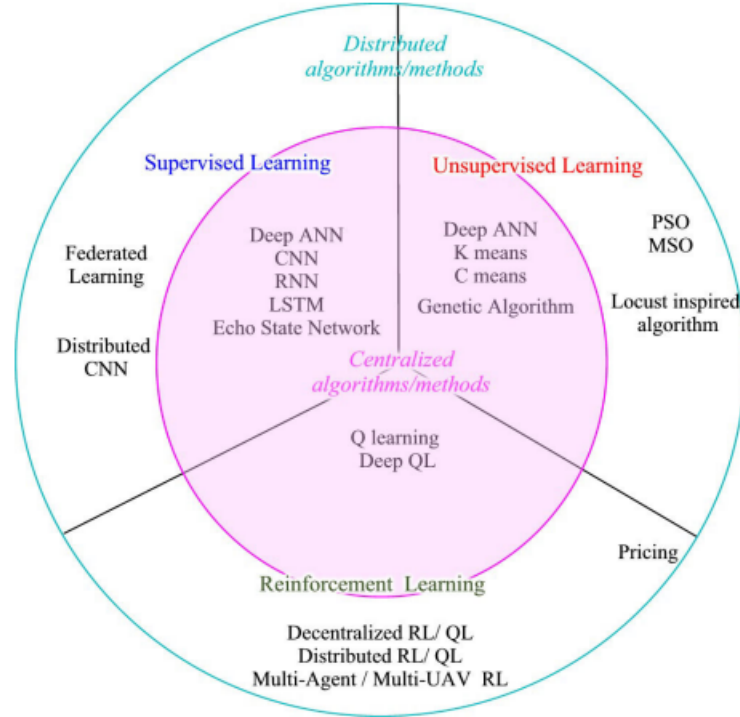


Figure 3.5: The literature review uncovered the primary methods used for the maintenance and automation of drones (Rina Azoulay et al, 2021).

For a review of time series models, see the summary by (Eric Zivot et al, 2005) and (Petros S. Bithas et al, 2019). Also, literature reviews to analyze methods in genetic transcription factors examine the time series (Ziv Bar-Joseph, 2012).

SUPERVISED MACHINE LEARNING

Neural networks were first proposed in 1944 by Warren McCulloch and Walter Pitts, two University of Chicago researchers who moved to MIT in 1952 as founding members of what is sometimes called the first cognitive science department (Larry

Hardesty, 2017). The neural nets described by McCullough and Pitts in 1944 had thresholds and weights but omitted layers, and the researchers did not specify any training mechanism (Larry Hardesty, 2017). Cornell University psychologist Frank Rosenblatt demonstrated the first trainable neural network, the Perceptron, in 1957 (Larry Hardesty, 2017).

LSTM

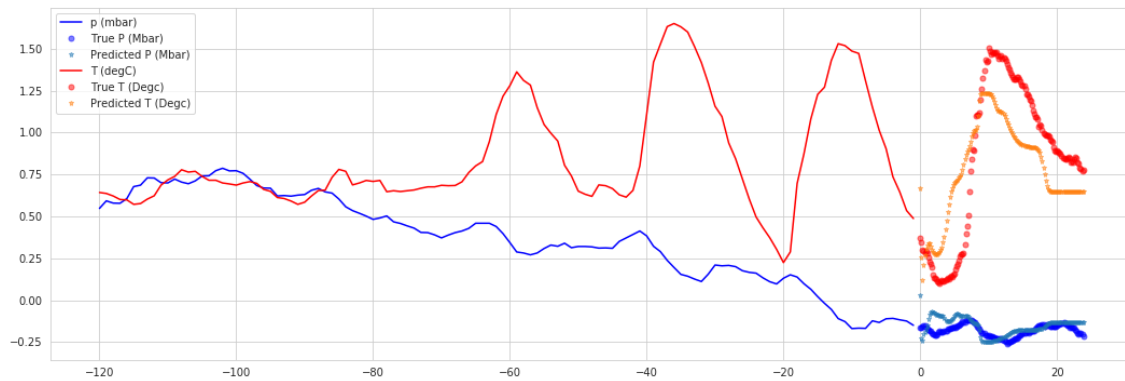


Figure 3.6: A convoluted LSTM generates a prediction for pressure and temperature (TensorFlow, 2022).

The Recurrent Neural Network (RNN) uses short and long-term memory to make sequence predictions. The specific model used is Long Short-Term Memory (LSTM), and LSTM is proven to be the best predictor for time series (Ihssan Tinawi, 2019). LSTM has three gates: scales input to cell (write), Output Gate, scales the output to cell, forget gate, and old cell value (reset). This model extends the memory of Recurrent Neural Networks, and it mitigates the vanishing gradient problem. The anomaly detection model is trained

and implemented as a multivariate time series prediction—Machine Learning techniques using concepts of Time Series Forecasting. Normalization significantly impacts accuracy and does not work well for short test data. There is good model accuracy with the MINMAX scaler (0,1) but terrible with the standard scaler (low, high).

UNSUPERVISED MACHINE LEARNING

Unsupervised methods use distance as a measure to detect anomalies, and distance is affected by learning rate, distance metrics, iterations, perplexity, and exaggeration. Detecting anomalies in multivariate systems can lead to misleading results, especially when trained incorrectly.

Relativity

$$\frac{1}{2} \frac{L}{c^2} v^2 = -K_1 + K_0 (\text{Albert Einstein, 1905})$$

Hamiltonia before derivative

$$W = -Et + S(x, y, z) (\text{Schrödinger, 1926})$$

Hamiltonia final form

$$i\hbar \frac{\partial \psi}{\partial t} = -\frac{\hbar^2}{2m} \frac{d^2 \psi}{dx^2} + U(x)\psi (\text{Fitzpatrick, 2016}) (\text{Farhan Rana, 2022})$$

Gradient Descent

$$x^{(k+1)} = -\eta^{(k)} \nabla f(x^{(k)}) + x^{(k)} (\text{Caramanis, 2012})$$

Assumptions

$$C \times change = - C * \nabla + C \times position, C = constants, \nabla = gradient$$

The Schrödinger (Schrödinger , 1926) and Einstein's relativity (Albert Einstein, 1905) equations are identical to gradient descent, when replacing the differences with constants (Sankar Das Sarma, 2019). Niels Bohr matrices can be interpreted as nodes (d) of hidden layers (n_H) and are represented as states in quantum mechanics (Sankar Das Sarma, 2019). Mass is made of energy and energy can have multiple states at the same time of superimposed fields and interact through forces to introduce emergent properties such as a nuclear unsupervised MLPs (Schrödinger , 1926). Gravitational and electric forces require a minimum mass of 2 for forces to be attracted or repelled and the same applies to Kolmogorov Theorem (Kůrková, V. 2003).

Multilayer perceptrons (MLP) have hidden layers (n_H), nodes (d) per hidden layers (n_H) and dendrites (w_{kj}, w_{ji}) while physical reality has mass ($m = \frac{E}{c^2}$) not hidden layers (n_H), (Albert Einstein, 1905) , nodes (d) as states (Schrödinger, 1926) and forces in place of dendrites (w_{kj}, w_{ji}) (Kůrková, V. 2003). The field of quantum mechanics has the measurement problem, lacks structure and whether states should represent anything in physical reality (Wayne Myrvold, 2022). The field of string theory declares topologies of strings in its equations. Topologies can take the form of hidden layers (n_H) of the MLP and strings as forces (w_{kj}, w_{ji}) (NLAB, 2021), (Bland-Hawthorn et al., 2021)). Forces are caused by energy with alternating states through superpositioning and can add up to zero by destructive interference.

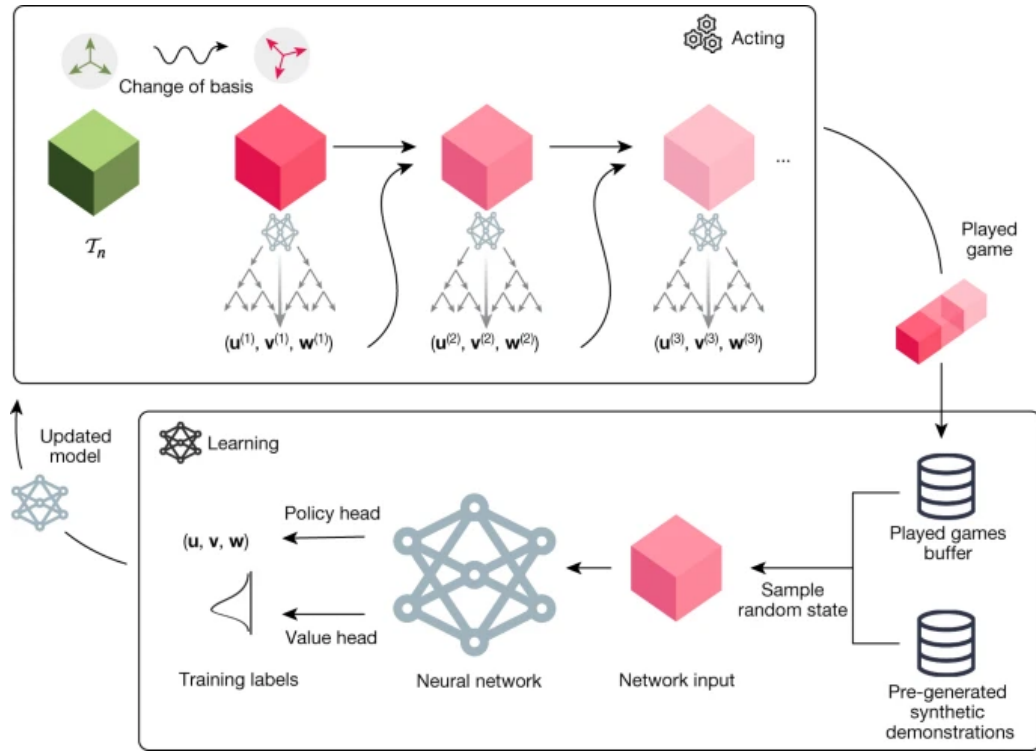


Figure 3.7: AlphaTensor Discovering faster matrix multiplication algorithms with reinforcement learning (Alhussein Fawzi et al, 2022) .

Furthermore, AI using reinforcement learning can generate equations that outperform gradient descent in specific hardware with zero prior hardware knowledge. However, AlphaTensor needs to pre-define a set of potential factors (Alhussein Fawzi et al, 2022) (Huimin Lu, 2017).

ASSOCIATION RULE MINING

Semantic rule mining alongside distance-based anomaly detection methods helps discover anomalous data (Wang Yin et al, 2015).

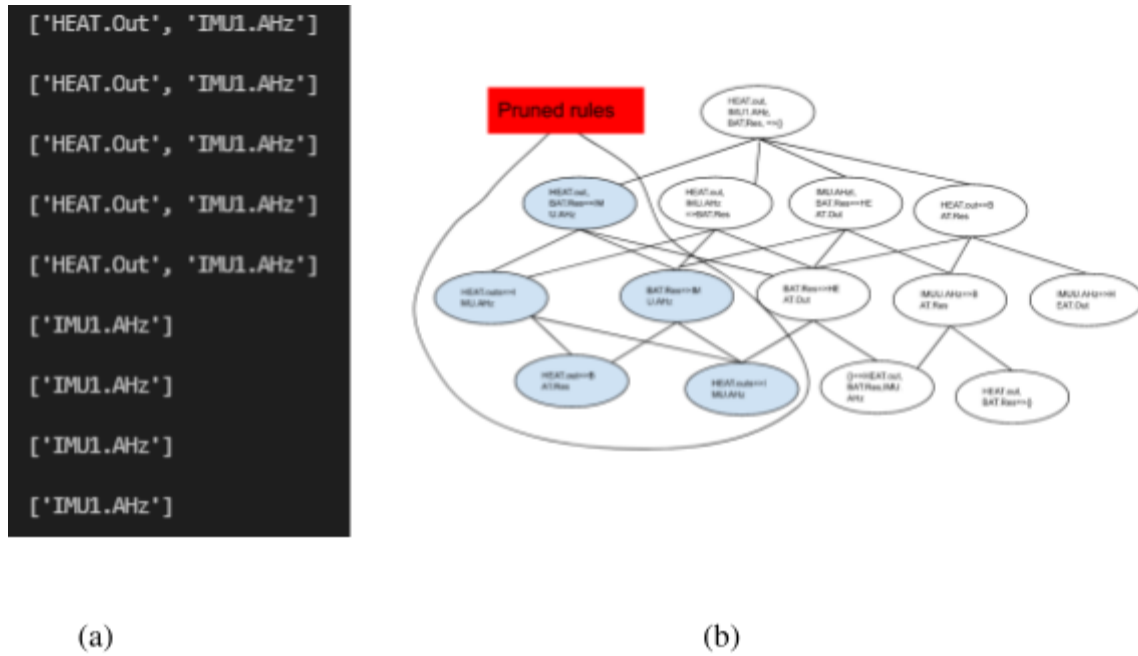


Figure 3.8: (a) Anomalies structured as transactions. (b) Transactions were evaluated for patterns and pruned.

A priori Algorithm will be used to associate various sensors that fail together and combine as precedent or consequent. The transactions list lists transactions with time as an index for feature anomaly count. Superimposing all sequences in a transaction model and evaluating minimum support and confidence has helped filter and generate unseen anomalies (Adam Hayes, 2022). A model can be filtered using all possible sigma thresholds one at a time superimposed in a transaction anomaly model.

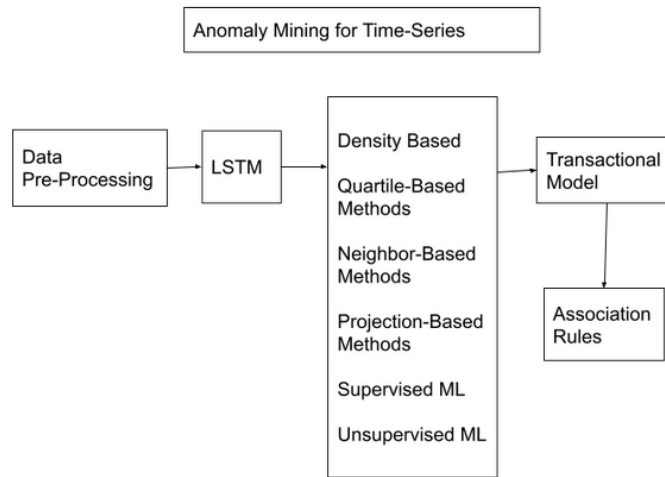


Figure 3.9: Ideal detection mechanism for anomaly detection.

Six sigma in association rules is used by filtering signals using six standard deviations to create a table per time index of all attributes beyond the threshold. Sequence extraction starts when signals oscillate outside the standard deviation thresholds of max and min from the mean. It uses Gaussian models to filter the signals using properties of normal distribution, such as a mean and standard deviation of attributes.

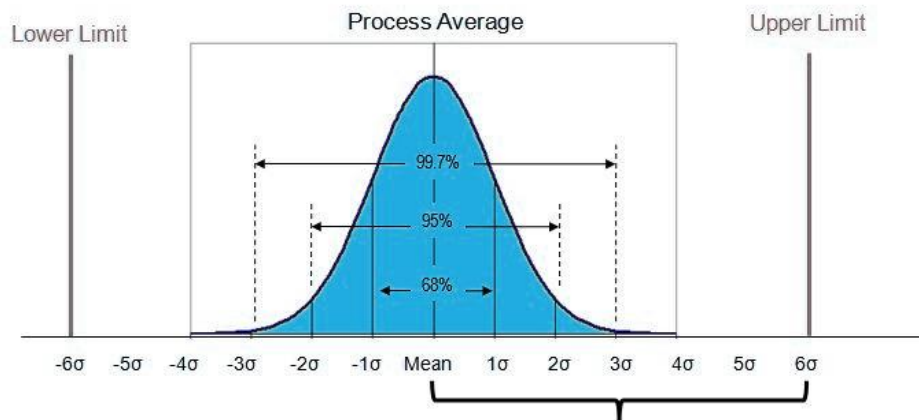


Figure 3.10: The LSTM predicted signals, aiming to filter the data to six standard deviations. In a typical process, 99.7% of the data density process is within three standard deviations.

Six sigma is the standard method for process improvement and a proactive method to maintain quality via an alteration to processes to keep the deviation below six standard deviations. 90% Confidence generates semantic associations with any support; therefore, any occurrence; generates rules of attributes interacting and triggering other variables as triggers. The rules are essential for forecasting future behavior and need a transaction list of anomalies.

CLUSTERING BASED ON T-SNE

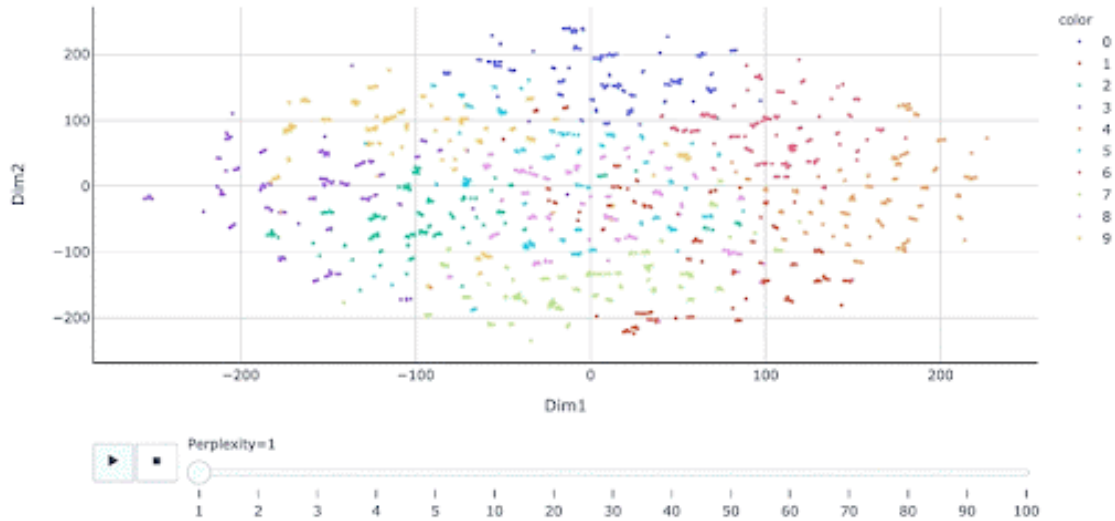


Figure 3.11: Neighbor based approach - t-SNE (Vegi, C., 2018).

The t-SNE algorithm is unsupervised and uses statistical Information from the data by creating cluster projections. The algorithm is based on gradient descent using distance as a metric. The visualization-based method generates high dimensional data into projections that are human-understandable.

DYNAMIC TIME WARPING

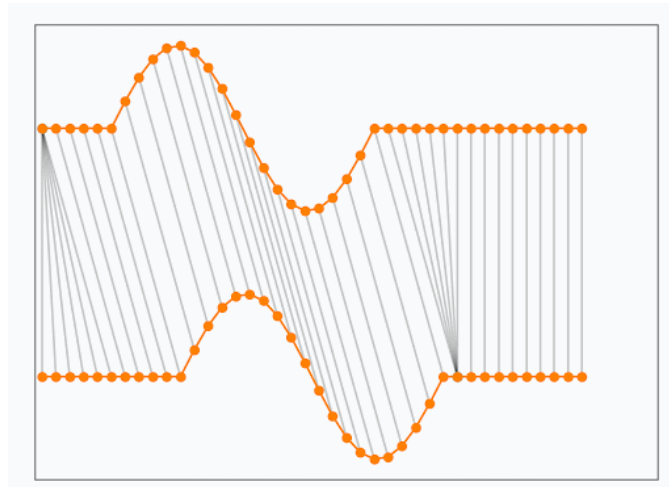


Figure 3.12: Dynamic time warping (Tavernard, R. 2022).

DTW space is more suitable for adversarial studies in the time-series domain than Euclidean distance (Belkhouja et al., 2022). Deep neural networks usually use time series with labels, and now labels are being replaced by DTW distance to automatically classify data when labels are unavailable. Also, Markov models have replaced DTW in fields such as speech recognition (Ellis D., 2012).

One of the difficulties in speech recognition is that although different recordings of the exact words may include more or less the same sounds in the same order, the precise timing - the durations of each subword within the word - will not match (Ellis D., 2012). As a result, efforts to recognize words by matching them to templates will give inaccurate results if there is no temporal alignment (Ellis D., 2012).

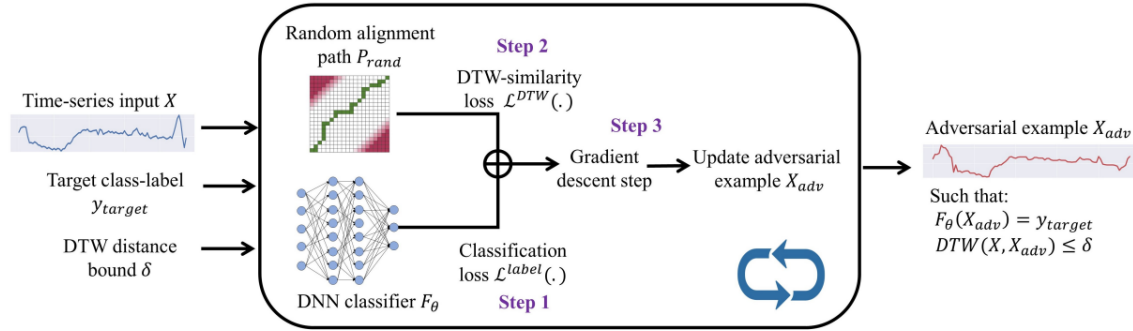


Figure 3.13: Dynamic time warping generates labels in deep neural networks without prior information, which helps classify information autonomously (Belkhouja et al., 2022).

The basic principle is to allow a range of 'steps' in the space of (time frames in sample, time frames in template) and to find the path through that space that maximizes the local match between the aligned time frames, subject to the constraints implicit in the allowable steps (Ellis D., 2012). Variable length comparisons for short and long signals. Better than euclidean distance with stochastic variables. Warps signals for best fit.

CONTRADICTIONS OF COLLECTIVE MODELS

The contradictory model can help create awareness of the time series' potential flaws. Changes to one model lead to modifications to variables in other models and affect measurement outcomes. Models can contradict themselves and provide complementary data that can be useful. Model contradictions can change over time; the variable's values contrast, and models can contradict. Contradictions lead to a problem in decision-making when discovering anomalies. Anomalies can be biased because of models and data that is

not fit correctly or do not represent the models. Average model predictors are a better way to detect anomalies in time series.

CHAPTER 4

SYSTEM COMPONENTS

4.1 COMPONENTS

4.1.1 BACKEND

The backend includes MAVlogDUMP and data cleaning— association mining, long-short-term-memory recurrent neural network, t-SNE, and Gaussian models.

4.1.2 FRONTEND

The section the user experiences is the front end and includes the visualization interface implemented using a flask server.

4.2 INTERFACE DESCRIPTION

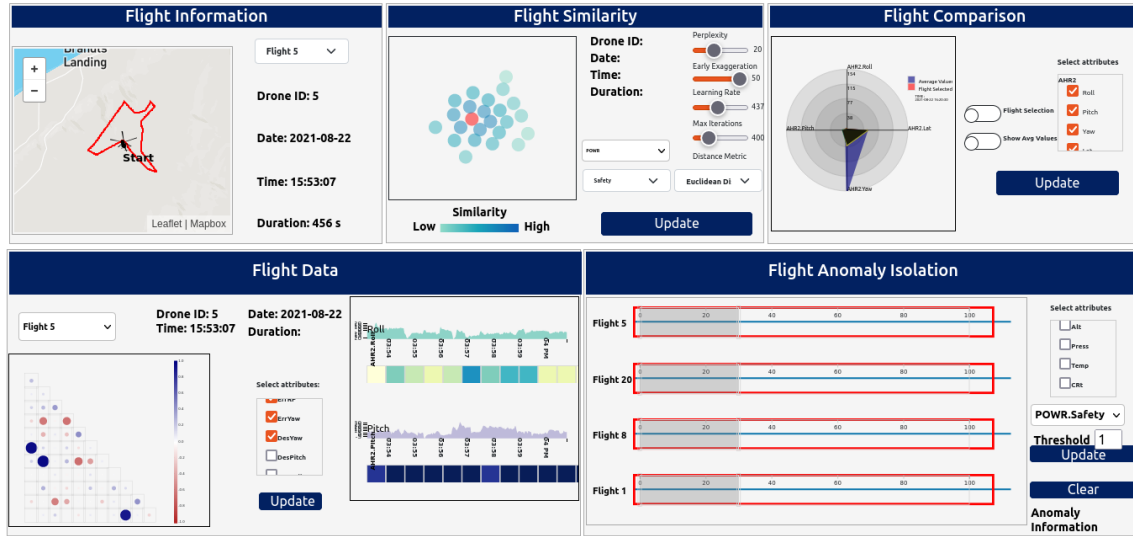


Figure 4.1: The main interface of the system.

4.2.1 IDIOM ABSTRACTION

The idiom for the drone flight analysis consists of a panel that will get input from the user on the data for visualization. The visualization consists of cluster analysis, plotting features, and visualizing the location of the flight with a time slider.

4.2.2 MAP

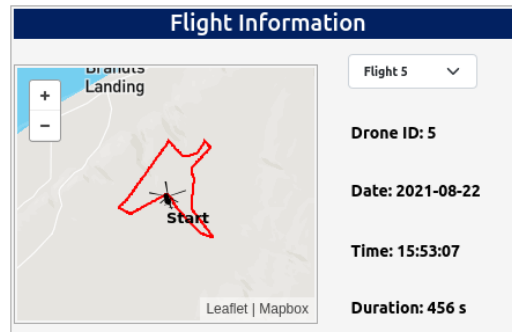


Figure 4.2: A map displaying drone movement.

An open-source Javascript library called Leaflet generated maps. For any selected flight, the map chart shows the animation of the path taken by the flight, and it results in a nice transition showing the path of the flight. The visualization of the map allows the user to zoom in and out of the map. The flight data contains GPS data of the flight with latitude and longitude. The coordinates are in increasing order of time; then, lines connect the points to the plot. These attributes and flight IDs were taken and converted into GeoJSON format to plot the map chart. LocationIQ fetches data, and it fetches the name of the city and the state of the starting point of the flight path. Mapbox is part of map implementation.

4.2.3 ATTRIBUTE CHARTS

The attributes chart section provides visualization for the attributes selected from the control panel for the selected flight. The attribute chart enables comparison between selected attributes. All the plotted attribute charts have a time slider, which indicates the flight duration and allows sliding to specific time points of the selected flight in the prototype. The charts are filled with contrasting, transparent colors to understand chart comparison. Upon selection, attributes are plotted and visualized. Plots were not the focus of the second prototype, and ArduPilot has the plotting capability. The attribute chart plots all charts in the second prototype and not the first. The initial prototype is augmented with a zoom function to allow closer inspection of individual charts.

4.2.4 CONTROL PANEL FOR FLIGHT SELECTION

Control Panel allows selections of flight and attributes to visualize, and the visualizations display according to the controls selected by the user in the control panel. In the second prototype, the control box differs from the initial prototype—new functional requirements and implementations change are added in the second phase of the research, such as a new interface.

4.2.5 TIME SLIDER

The time slider is successful in the prototype. It allows the user to track drone behavior over time in an interactive way quickly, and the user can get a better feel for how the drone behaves over time. This feature allows visualizing behavior related to time in the slider, such as plots in the prototype. However, the time slider format is in seconds, and due to nan values, there are missing slices of data with comparisons. The slider has bugs due to a need for an understanding of requirements.

4.2.6 T-SNE

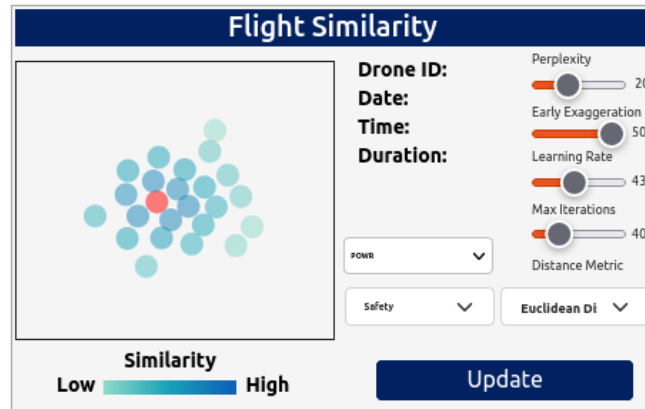


Figure 4.3: This feature allows us to find flights with similar behavior concerning the selected flight.

The t-SNE can position the selected flight among all the other flights where the center is all flights should ideally be, indicating optimal performance with the attributes selected. However, changing variables changes the results observed and can confuse users. The t-SNE functions independently of all the other models and does not use distance or standard deviation, and t-SNE is a projection.

4.2.7 RADAR

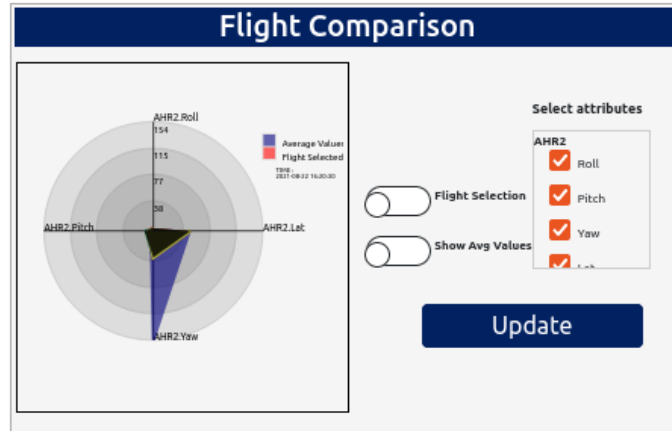


Figure 4.4: A radar chart displaying distributions correlations of attributes.

The chart displays the comparison between the average values and the values of flights at a specified timestamp. The mean values for all the attributes and the selected attributes, i.e., AHR2 (Pitch, Roll, Yaw, Lng), merge into one plot. The chart is limited to visualizing up to 7 characteristics at a time. The visualization resets on clicking the update button, which has severe bugs. A legend is displayed showing the color-coded description. The Radar Chart compares the selected flight and its attributes with the average values of all the flights. Attribute visualization occurs against each axis, and then a shape is formed by connecting the resulting dots.

4.2.8 HEATMAP

The heatmap shows each window of an attribute for each second in time Figure 4.5 right, where a value's color depends upon its deviation from the predicted value.

There are two heatmaps. One heatmap uses a correlation matrix and the other displays data frames per second of time.

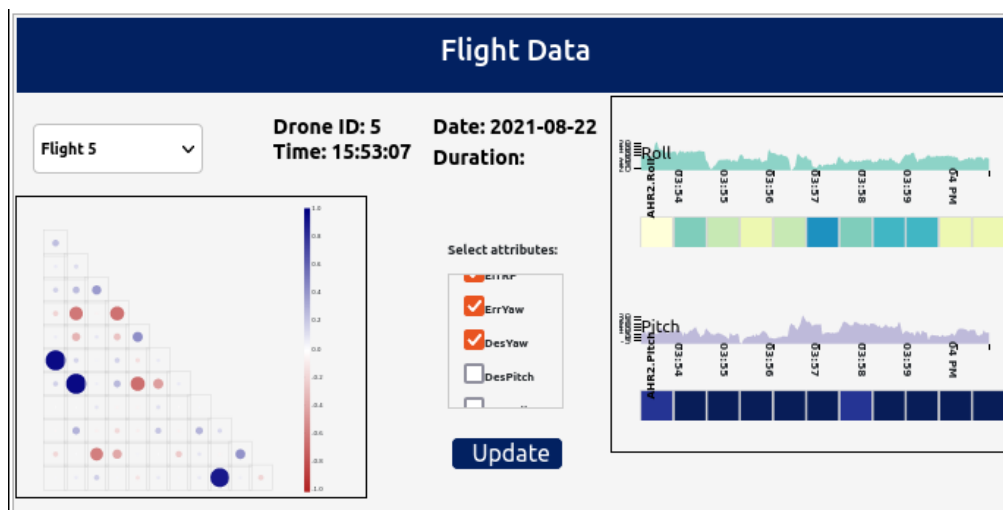


Figure 4.5: A heatmap and plots displaying correlations.

4.2.9 FLIGHT ANOMALY ISOLATION

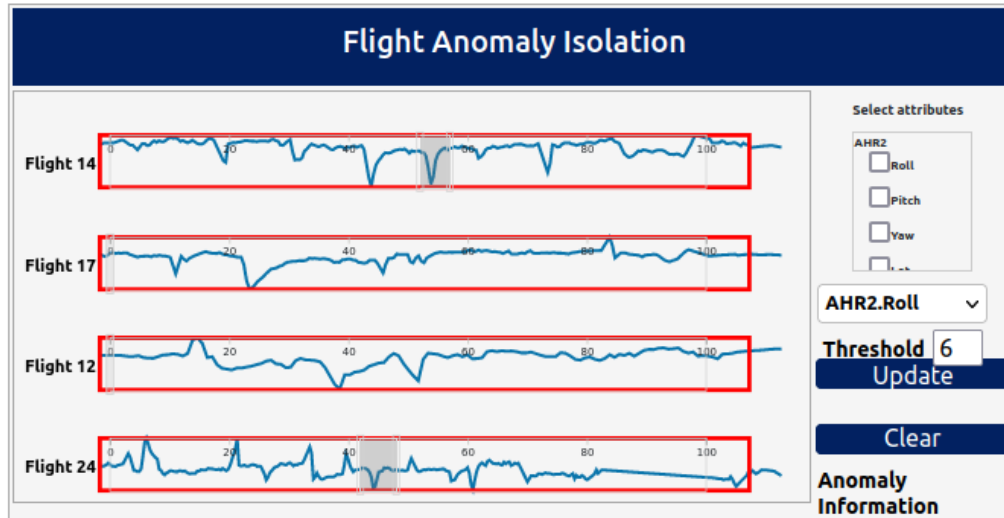


Figure 4.6: Graph showing attributes with user-defined standard deviation and similarities. Users can highlight subgraphs with the mouse and search for patterns.

The Flight Anomaly Isolation panel shows selected flights based on their similarity, calculated using Dynamic Time Warping. Dynamic time warping uses similarity. In-flight Anomaly isolation, all flights are ranked from highest similarity to lowest similarity from the mean of all attributes. Dynamic time warping is independent of the mean and standard deviation; the mean and standard deviation classified anomaly flags and only appear or disappear by changing the standard deviation threshold.

CHAPTER 5

ANALYSIS AND CASE STUDIES

5.1 ANALYSIS

For this first case study, we load several drone flights into the interface. Flights 4,10,11,21, and 23 had a short duration. Problems found include Inertial Measurement Unit data (IMU), GPS accuracy information (GPA), Information received from compasses (MAG), Gathered battery data (BAT), System power information (POWR), IMU Heater data (HEAT), and Attitude Control oscillation monitor diagnostics (CTRL). The t-SNE for power safety displays flights 4, 3, 23, 21, 10, and 11 at a further distance from all flights and are less similar from the mean. The magnetic behavior for flight 21 is less similar to all flights, and flights 10, 3, 11, and 23 are in the external cluster where most flights are closer in similarity. 25% of the flights analyzed had noticeable problems using six standard deviations.

All flights that did not appear to change position in the GPS graph correlate to battery, safety, and magnetic problems. When plotting the GPS coordinates for each flight, it becomes apparent that flights vary in duration, short flights are anomalies, and short flights were not part of expectations. The shortest flight durations have co-occurring

sequences of anomalies leading to other forms of anomalies. The data from the heatmap and semantic rules support the sequential anomalies inside the drone. The heatmap helped identify anomaly association rules for selected flights. It is not apparent that sequences of problems are occurring and interacting or causing other anomalies. To further understand, t-SNE compares the flights and asserts if associations are presently by using additional models in the interface. Precedent and the consequent rule-based system do better than LSTM, such as apriori, when there is short or missing data.

5.1.1 MINMAX SCALER

Normalization style had a significant effect on accuracy. For example, MinMax, compared to the standard scaler, was better at predicting when the data included zero values.

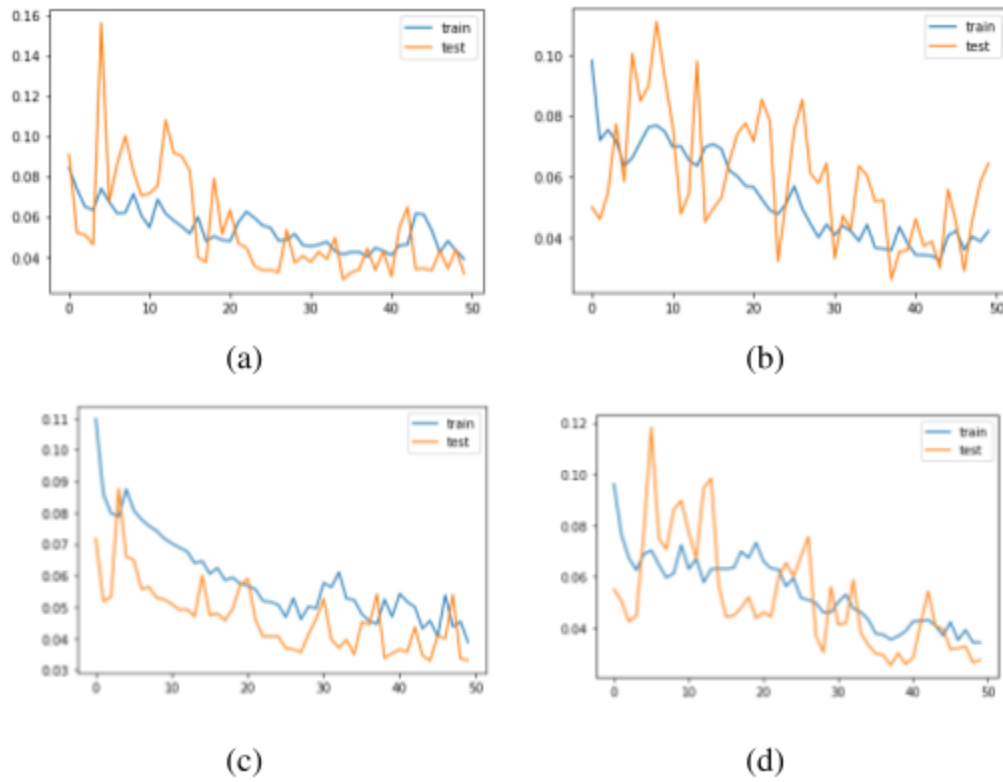
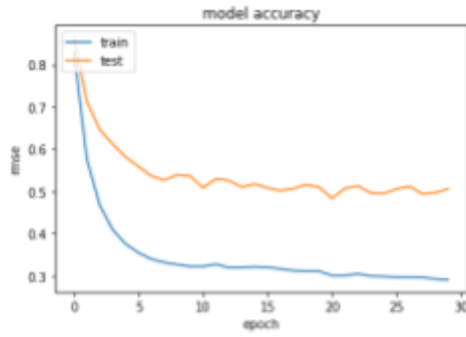


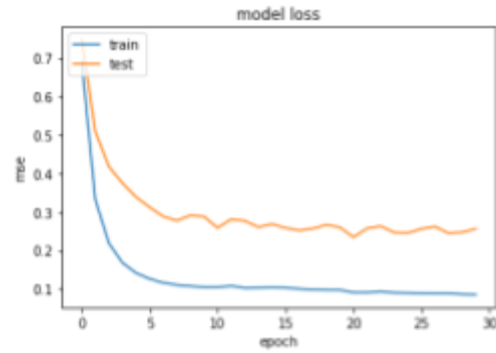
Figure 5.1: (a) 10 backsteps. (b) 50 backsteps. (c) 500 backsteps. (d) best minmax model.

5.1.2 STANDARD SCALER

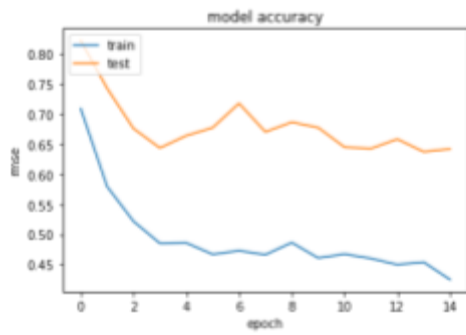
This method included the worst accuracy because there was missing data and zero values that affected the distribution when the data was normalized.



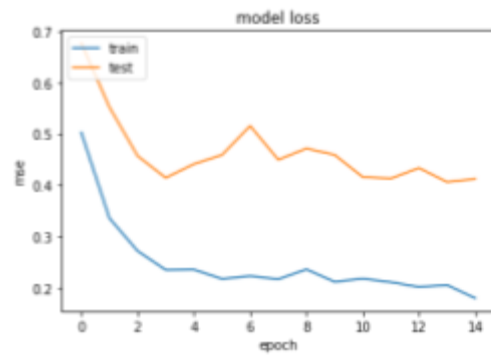
(a)



(b)



(c)



(d)

Figure 5.2: (a) Model 5. (b) model 5. (c) Model 6. (d) Model 6.

5.1.3 ASSOCIATION MINING

The Apriori algorithm used for associations is a library and not implemented from scratch. Initially, it needed to be clarified on the best method to convert anomalies into a transactional format since there are multiple features and timestamps. The simplest method was to convert it to a format similar to previous transactional data over time (Gaurav N. Pradhan, 2017) (T. Schlüter and S. Conrad, 2011).

5.2 CASE STUDIES

5.2.1 CASE STUDY 1 - FLIGHT 2

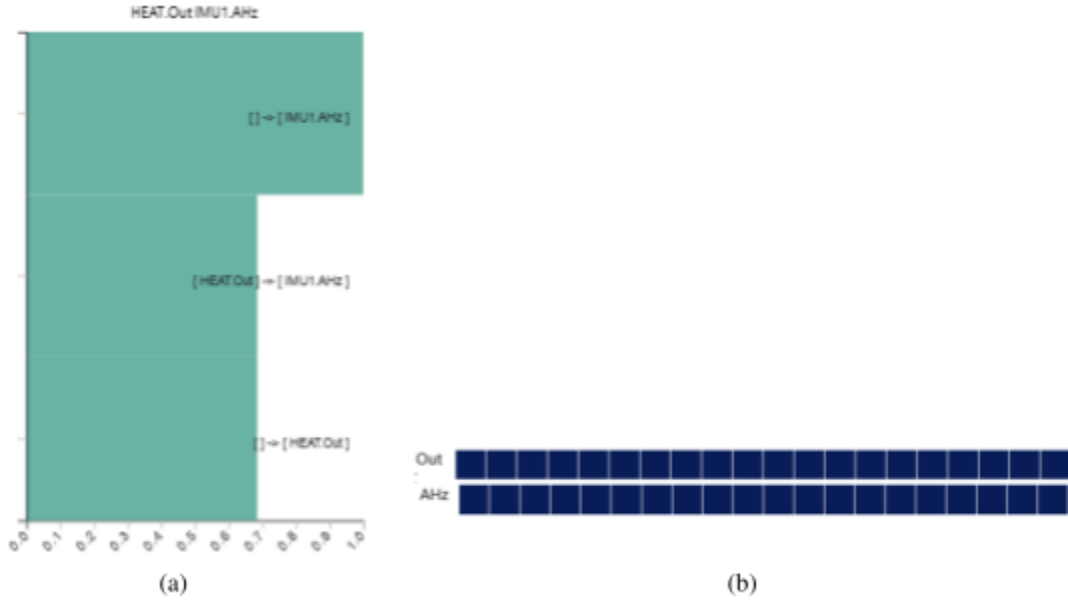


Figure 5.3: (a) The flight is loaded and rules generated. Apriori gives an association rule for heat out and AHZ (vibrations). (b) The user looks at the heatmap of those attributes over time to confirm the readings.

First, we examine flight 2 to identify any possible anomalies. In order to isolate attributes of interest, we initially perform association rule mining over flight readings. We discover an association rule between the HEAT OUT attribute, which refers to the IMU heater data controller output to the heating element, and the AHZ attribute, which refers

to the Inertial accelerometer measurement rate. HEAT Out occurs in issues related to the heat controller in the drone. The controller is acting out due to overheating, while moving fast. Attempts to cool the drone occur when drones experience some event or issue that causes the heat controller to trigger. For instance, if the external temperature of the drone's route is too hot, or there are temperature fluctuations in the topological area flown, then there is stress on the drone sensors, which in extremes can cause them to freeze or melt. For example, Air France flight 4590 caught on fire when wires made contact with a ruptured fuel tank (LOGEMENT, M. D. L. D. T. E. D., 2001.). We further examine via the heatmap in Figure 5.3 (b) that these attributes show anomalous behavior over the same time stamps.



Figure 5.4: (c) The user plots the flight path to check how this manifests with other models. (d)

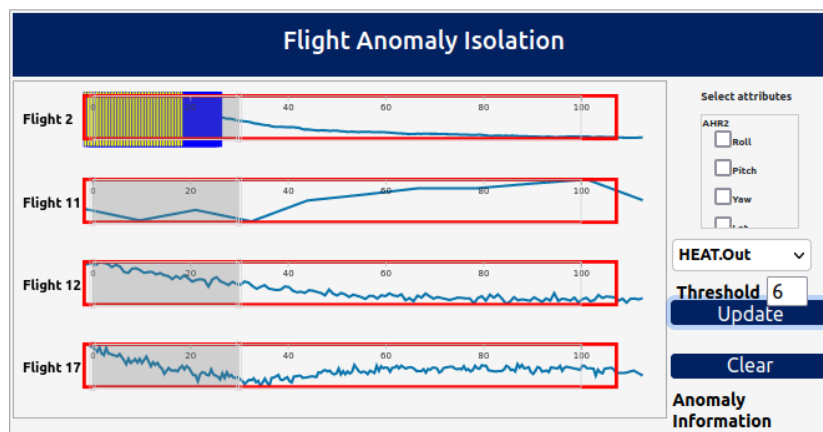


Figure 5.5: The anomaly isolation view provides a view of heat out. Findings: flight 2, 11 are similar, and flight 2 had flagged anomalies.

Similarly, we can identify power safety issues in flight 4, 10, 21, 23, and 11. GPS accuracy in flight 18. The user wants to verify the rule. The problem is heat out; therefore the inertia of the drone has a temperature controller pumping heat greater than normal. Next, we examine the drone's flight path in Figure 5.4 (c) to gauge how severe the anomaly's impact on the drone has been.

Despite a mild anomaly in the HEAT OUT and AHZ attributes, the drone still completes a successful flight. We, therefore, seek to verify the association rule found by examining the behavior of this flight about other drone flights for the same HEAT OUT attribute. We do this by clustering the drone flights using a t-SNE plot, as shown in Figure 5.4 (d). The selected drone flight, highlighted in red, is further away from the other flights in the cluster, indicating the discovery of a definite anomaly.

Subsequently, we drill down into flight 2's statistics in Figure 5.5 and see that over the ~4-minute period of flight 2; there are anomalies regularly flagged for the first 60-70

seconds, where there is more inertial heat being pumped out of the drone than is normal behavior. In the flight path in Figure 5.4 (c), we can see that a sudden turn is reflected halfway into the flight; anomalous inertial behavior is occurring. Furthermore, in this view, we can compare other drone flights against the selected flight in a one-to-one manner. We see that flight 11 shows very similar behavior to the anomalies reflected in flight 2. We, therefore, look further into flight 11 anomalies in the subsequent case study.

5.2.2 CASE STUDY 2 - FLIGHT 11

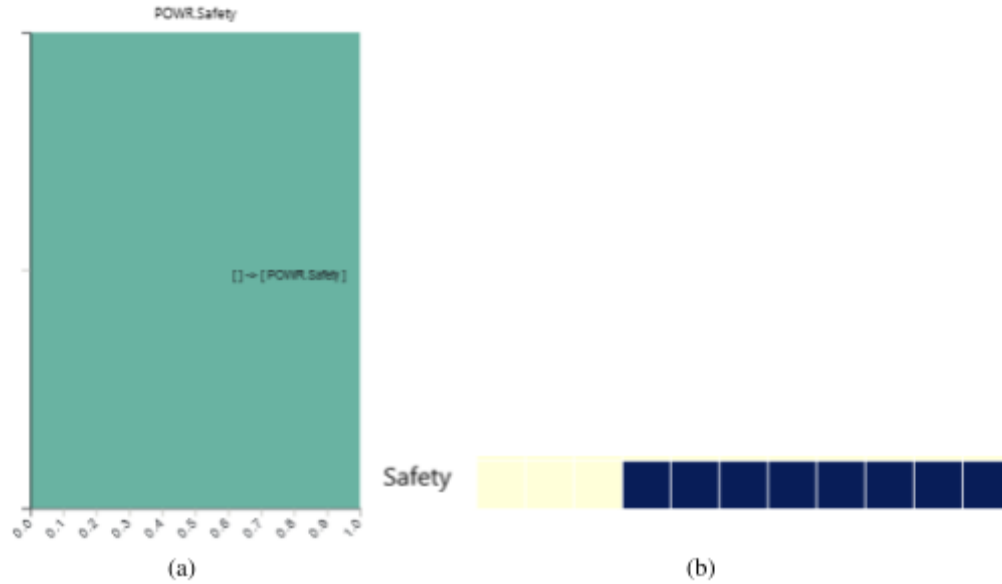


Figure 5.6: (a) Power safety associations won't show below 6 standard deviations and included binary flags only. (b) Safety is triggered multiple times and not enough information is known.

First, we examine flight 11 to identify any possible anomalies. In order to isolate attributes of interest, we initially perform association rule mining over flight readings. We have yet to discover an association rule for POWR Safety which refers to the safety of the power distribution. Power safety problems occur on short flights with approximately 10 seconds of data. This problem occurs when drones experience some event or issue that causes the power to fail. For instance, the battery resistance fails because of mechanical wear in the wires, vibrations displacing conducting materials, magnetic effects on the circuits, and current leakage. We further examine via the POWR Safety in Figure 5.6 (b)

that these attributes do not show anomalous behavior over the same time stamps with other attributes.

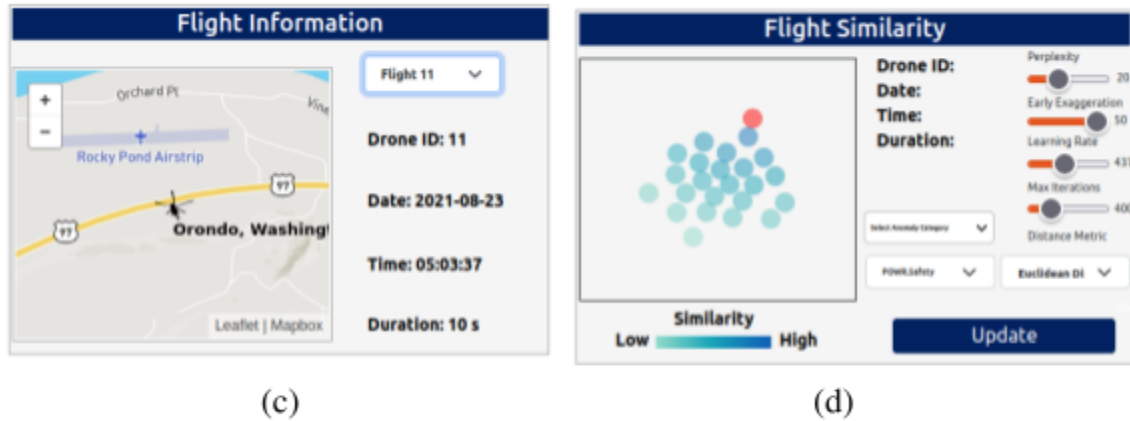


Figure 5.7: (c) The flight is short at 10 seconds. Flights don't usually last a couple of seconds. (d) Power safety is different from all others and closer to the outside of cluster.

Next, we examine the drone's flight path in Figure 5.7 (c) to gauge how severe the anomaly's impact on the drone has been. We see that the drone did not complete a successful flight, and there is a mild anomaly in the POWR Safety attributes. We, therefore, seek to verify the association rule found by examining the behavior of this flight to other drone flights for the same POWR Safety attribute. We do this by clustering the drone flights using a T-SNE plot, as shown in Figure 5.7 (d). The selected drone flight, highlighted in red, is further away from the other flights in the clustering, indicating the discovery of a definite anomaly.

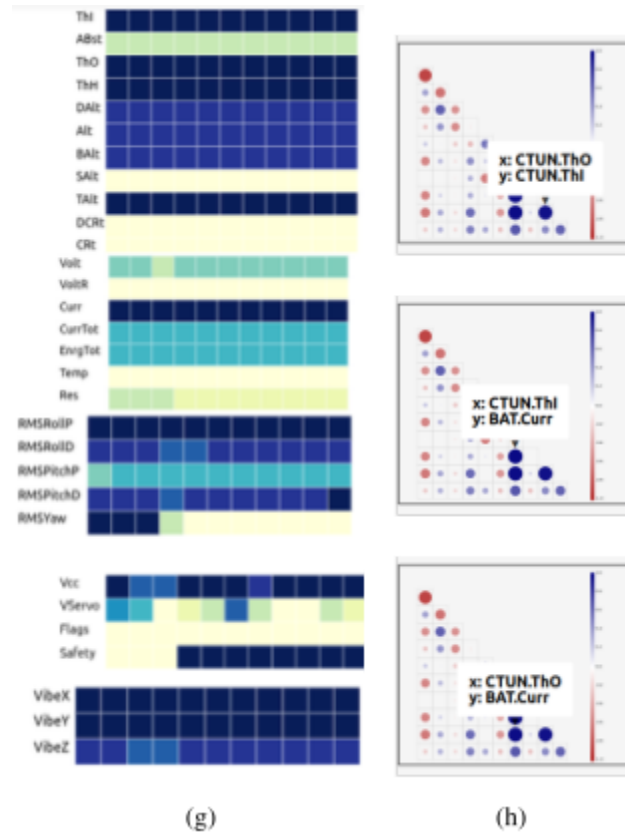


Figure 5.9: (g) at low thresholds human perception is overloaded when sigma is below 6 standard deviations. (h) Perception overload is helped by reducing variables visually using a correlation matrix.

The standard deviation was lowered below six standard deviations to allow for attributes not to be removed by the filter. There were over ~30 attributes shown in Figure 5.9 (g), which caused less confusion compared to not having any data in Figure 5.6 (a). The heatmap revealed problems with the throttle CTUN ThO and the controller, known as the power or fuel controller.



(l)

(m)

Figure 5.10: **(l)** VIBE stands for processed (acceleration) vibration information, and VibeY occurs in the y-axis. **(m)** CTUN stands for Control Tuning information, and ThI is throttle input.



(n)

(o)

Figure 5.11: **(n)** CTUN stands for Control Tuning information and Tho throttle output. **(o)** CTRL stands for Attitude Control oscillation monitor diagnostics, and RMSRollP is LPF Root-Mean-Squared Roll Rate controller P gain.

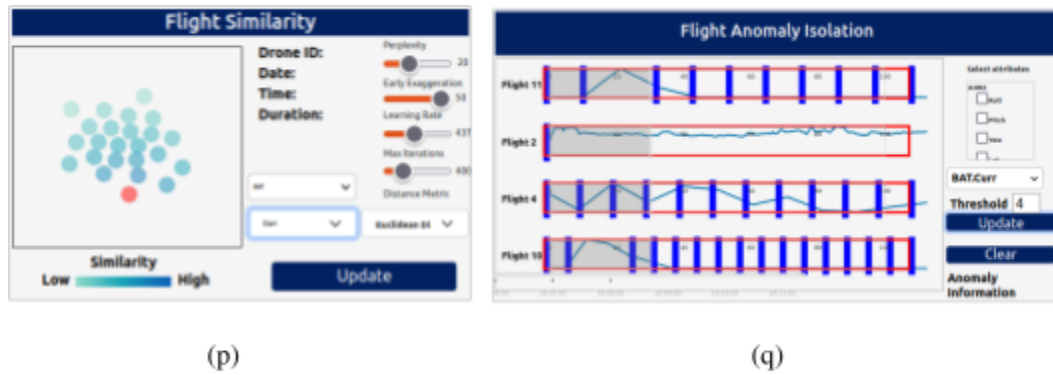


Figure 5.12: (p) BAT stands for gathered battery data, and the Curr is measured current (q) BAT Curr using a standard deviation of 4.

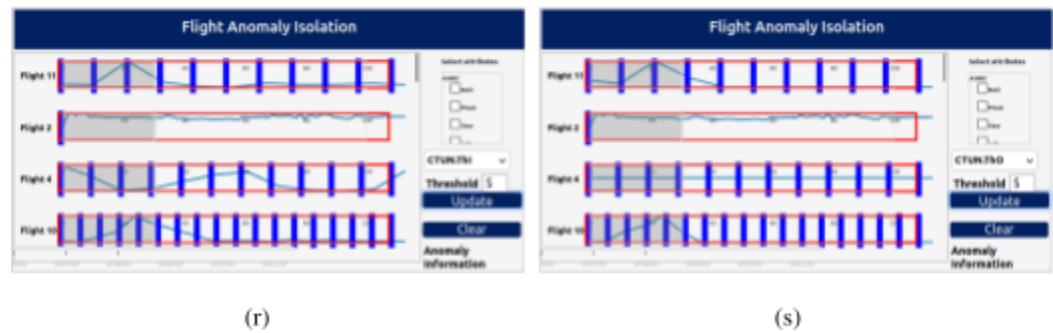


Figure 5.13: (r) CTUN CTUN stands for Control Tuning information and ThI throttle input. ThI (s) CTUN stands for Control Tuning information and ThO throttle output. .



Figure 5.14: **(t)** CTRL stands for Attitude Control oscillation monitor diagnostics, and RMSRollP is LPF Root-Mean-Squared Roll Rate controller P gain. **(u)** VIBE stands for processed (acceleration) vibration information, and VibeY occurs on the y-axis.

The throttle controller Figure 5.13, which control power with vibrations Figure 5.14 (u) and high roll Figure 5.14 (t), lead to problems with the battery Figure 5.12. Flight 11 and 2 are similar without taking into account sigma into the model as shown in all the flight anomaly association sections.

CHAPTER 6

RESULTS AND IMPLICATIONS

In many cases, the interface made it relatively easy to investigate anomalies in flights. Visualization allows for juxtaposing flights against each other to find familiar sources of faults. In our studied set of flights, ideal flights that moved on GPS and do not have anomaly patterns at six standard deviations, 12.5% of total flights; three were within perfection. Most flights that moved on GPS have a pattern of anomalies that is 66.67% of total flights and did not cause significant failures because they flew over 7 minutes, 16 flights. Five flights that did not move on GPS have anomalies, and 20.83% of total flights caused significant failures within 10-seconds. Anomalies exist below 90% confidence, and at or above six σ . 4.17% of flights had critical anomalies below six σ *such as* at four σ and limited flight time to less than 11 seconds. One flight failed below six standard deviations, and all others followed a normal distribution with failures at or above six standard deviations.

6.1 LIMITATIONS

The process standard "Lean Six Sigma" using six standard deviations is not 100% the best "fit all method" because it omits critical problems below the six standard deviation threshold. The data was not normalized, and it is unknown if this impacts data analysis due to the A priori algorithm removing noise through the most frequent itemset. Band-Pass Filter in the frequency domain better represents data by removing noise, and attributes in the time domain and not the frequency domain are filtered. The distance and similarity change with the algorithms used for distance comparison.

6.2 CHALLENGES

A significant challenge in employing supervised and unsupervised methods is that short test data leads to noisy predictions. The drone operator needs to capture data pre-flight to estimate a good baseline, and the best models will not do better than a mean prediction of data. The concerns are that predictions are short, and when problems occur, they are not different seconds into the future. Also, flights with 10 seconds of data are unreliable predictors due to human error in collecting data. It is not apparent to see relationships because thresholds might sometimes need to reflect the sensitivity. Outliers skew the data. By comparing these attributes using area charts and observing intricate changes by navigating to specific time points in the chart using multiple models, we can

incisively understand. Real-time data integration requires significant backend engineering—human error in drone operation makes it more challenging.

6.3 CONCLUSION

Unfiltered data is misleading in estimating anomaly problems, assuming using only standard deviation as a measure. Furthermore, association mining rules accurately describe problems with flights. The prototype was successful, and semantic rule mining correctly identifies sequences of anomalies affecting system behavior. Anomalous associations at low thresholds detect sequences that lead to consequent behavior using the apriori algorithm to filter the data a second time after filtering using standard deviation. The heat map affirms the behavior for anomalous rules occurring in sequences; the radar chart compares the selected flight's value with the mean value of all flights and t-SNE displays flights with similar distances concerning the chosen flight. Heat map confirms associated rules and does not display co-occurrences directly as association mining does. It would be reasonable to assume that if a user is attempting to fly a drone that a short-duration flight is due to problems. Users optimally want to fly a drone and maintain a flight duration for maximum flight duration.

Drones are affected by vibrations, magnetic disturbances, and the weather can

destroy them. Designing equipment that considers electromagnetic property is a novel approach that saves money. Electronic design can accidentally become an antenna due to its surface accumulating charge and will cause wave perturbations affecting the equipment. System design will improve autonomous systems by taking into account electromagnetic properties. Controlled oscillations of these wave properties by varying atomic orbitals will, in the future, replace inert materials. Electromagnetic drives can help replace materials by controlling the wave range varying over time, causing equipment failures.

Dense materials block radiation, such as lead. However, even thick materials oscillate due to atomic properties. Also, Electromagnetic flux reduction is associated with drop electromagnetic momentum reduction and, therefore, resistance that will help generate electromagnetic convergence, ideally reaching zero flux in the future. A zero Electromagnetic flux would mean space equipment operating ideally with no anomalies in respect to the electromagnetic waves (Kenneth A. LaBel, 2004).

REFERENCES

- Ignatov, A.M. Plasma Crystal as a Time Crystal. *Plasma Phys. Rep.* 47, 139–147 (2021).
<https://doi.org/10.1134/S1063780X21020033>
- Stødle, D., Borch, N. T., Solbø, S. A., & Storvold, R. (2014). High-performance visualization of UAV sensor and image data with raster maps and topography in 3D. *International Journal of Image & Data Fusion*, 5(3), 244–262.
<https://doi-org.ezproxy1.lib.asu.edu/10.1080/19479832.2014.907363>
- Fawzi, A., Balog, M., Huang, A. *et al.* Discovering faster matrix multiplication algorithms with reinforcement learning. *Nature* 610, 47–53 (2022).
<https://doi.org/10.1038/s41586-022-05172-4>
- H. Lu, Y. Li, S. Mu, D. Wang, H. Kim and S. Serikawa, "Motor Anomaly Detection for Unmanned Aerial Vehicles Using Reinforcement Learning," in *IEEE Internet of Things Journal*, vol. 5, no. 4, pp. 2315-2322, Aug. 2018, doi: 10.1109/JIOT.2017.2737479.
- S. C. Pais, "The Plasma Compression Fusion Device—Enabling Nuclear Fusion Ignition," in *IEEE Transactions on Plasma Science*, vol. 47, no. 11, pp. 5119-5124, Nov. 2019, doi: 10.1109/TPS.2019.2942997.
- Eric Zivot, 2005. <https://faculty.washington.edu/ezivot/econ584/notes/nonlinear.pdf>
- Bithas, Petros S., Emmanouel T. Michailidis, Nikolaos Nomikos, Demosthenes Vouyioukas, and Athanasios G. Kanatas. 2019. "A Survey on Machine-Learning Techniques for UAV-Based Communications" *Sensors* 19, no. 23: 5170.
<https://doi.org/10.3390/s19235170>
- Do, Y., & Lai, Y-C. (2005). Scaling laws for noise-induced superpersistent chaotic transients. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, 71(4), [046208]. <https://doi.org/10.1103/PhysRevE.71.046208>
- Pradhan, G. N. and B. Prabhakaran, “Association rule mining in mul-tiple, multidimensional time series medical data - journal of healthcare informatics research”, URL <https://link.springer.com/article/10.1007/s41666-017-0001-x> (2017).

Hennig, D., R. Uddin, S. Suneet, C. Lange and A. Dokhane, 2020. “To the special issue: Nonlinear nuclear reactor stability analysis and special aspects of modeling of complex dynamical systems (principles of model order reduction). special issue on nonlinear stability analysis”, URL <https://experts.illinois.edu/en/publications/to-the-special-issue-nonlinear-nuclear-reactor-stability-analysis>.

RINA AZOULAY, 2021. <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9557265>

Wang, Y., D. Wang and J. Wang, 2014. “A data driven approach for detection and isolation of anomalies in a group of uavs”, URL <https://www.sciencedirect.com/science/article/pii/S1000936114002027>

Tinawi, I., 2019. URL <https://dspace.mit.edu/bitstream/handle/1721.1/123129/1128282917-MIT.pdf?sequence=1>.

Sarma, . P. T. . M. . S. D., 2012. URL <https://arxiv.org/pdf/1903.03516.pdf> (2019).

LaBel, K. A., 2004. URL https://nepp.nasa.gov/DocUploads/392333B0-7A48-4A04-A3A72B0B1DD73343/Rad_Effects_101_WebEx.pdf.

HK;, P. K. E., 2021. “Unsupervised fault detection on unmanned aerial vehicles: Encoding and thresholding approach”, URL <https://pubmed.ncbi.nlm.nih.gov/33809830/> (2021).

FLUKE, 2004. URL https://www.testequipmentdepot.com/application-notes/pdf/power-quality/electrical-noise-and-transients_an.pdf.

Hayes, A., 2022. “What is a confidence interval and how do you calculate it?”, URL <https://www.investopedia.com/terms/c/confidenceinterval.asp>.

Christ, K. (2021, November 23). Swords and shields: Autonomy, ai, and the Offense-Defense Balance. Retrieved November 11, 2022, from <https://gjia.georgetown.edu/2021/11/22/swords-and-shields-autonomy-ai-and-the-offense-defense-balance/>

Craig Whitlock, 2014. When drones fall from the Sky. (n.d.). Retrieved November 11, 2022, from <https://www.washingtonpost.com/sf/investigative/2014/06/20/when-drones-fall-from-the-sky/>

Aquilina, R. (2022, July 13). Lessons from use of drones in the Ukraine War. Retrieved November 11, 2022, from <https://www.droneshield.com/blog-posts/lessons-from-drones-in-ukraine-war>

Ally Foster, 2019. The pocket-sized drone changing the way the military operates - heraldsun. (n.d.). Retrieved November 12, 2022, from <https://www.news.com.au/technology/innovation/military/the-pocketsized-drone-changing-the-way-the-military-operates/news-story/542cd2f14741a002eb06b58cde9a078c>

PanosCs. (2022, June 01). DJI Agriculture GIF - DJI Agriculture Drone - discover & share gifs. Retrieved November 11, 2022, from <https://tenor.com/view/dji-agriculture-drone-drones-uav-gif-25835022>

David J Bromley. (n.d.). Retrieved November 11, 2022, from <https://www.people.vcu.edu/~djbromle/color-theory/lecture/6.html>

Saffo, D., Leventidis, A., Jain, T., Borkin, M. A., & Dunne, C. (2020, May 12). Data comets: Designing a visualization tool for analyzing autonomous aerial vehicle logs with grounded evaluation. Retrieved November 11, 2022, from <https://arxiv.org/abs/2005.06011>.

Tavenard, R. (n.d.). *An introduction to dynamic time warping*. Retrieved November 11, 2022, from <https://rtavenar.github.io/blog/dtw.html>

Taylor Kubota, 2021. *Time Crystal in a quantum computer*, *Stanford News*. Available at: <https://news.stanford.edu/2021/11/30/time-crystal-quantum-computer/> (Accessed: November 12, 2022).

Belkhouja, T., Yan, Y., and Rao Doppa, J., “Dynamic Time Warping based Adversarial Framework for Time-Series Domain”, *arXiv e-prints*, 2022.

Vegi, C. (2018, September 26). Visualizing Higher Dimensional Data using T-SNE on tensorboard. *Medium*. Retrieved November 12, 2022, from <https://medium.com/@vegi/visualizing-higher-dimensional-data-using-t-sne-on-tensorboard-7dbf22682cf2>

T. Schlüter and S. Conrad, 2011. "About the analysis of time series with temporal association rule mining," *2011 IEEE Symposium on Computational Intelligence and Data Mining (CIDM)*, pp. 325-332, doi: 10.1109/CIDM.2011.5949303.

Güldenring, J., Gorczak, P., Eckermann, F., Patchou, M., Tiemann, J., Kurtz, F., & Wietfeld, C. (2020, May 1). Reliable long-range multi-link communication for Unmanned Search and rescue aircraft systems in beyond visual line of sight operation. *MDPI*. Multidisciplinary Digital Publishing Institute. Retrieved November 12, 2022, from <https://www.mdpi.com/2504-446X/4/2/16/htm>

Bar-Joseph, Z., Gitter, A. & Simon, I. Studying and modelling dynamic biological processes using time-series gene expression data. *Nat Rev Genet* 13, 552–564 (2012). <https://doi.org/10.1038/nrg3244>

Myrvold, W. (2022) *Philosophical issues in quantum theory*, *Stanford Encyclopedia of Philosophy*. Stanford University. Available at: <https://plato.stanford.edu/entries/qt-issues/#MeasProbForm> (Accessed: November 12, 2022).

Ellis, D. (n.d.). Dynamic Time Warp (DTW) in Matlab. *Dynamic Time Warp in Matlab*. Retrieved November 12, 2022, from <https://www.ee.columbia.edu/~dpwe/resources/matlab/dtw/>

Larry Hardesty, 2017. <https://news.mit.edu/2017/explained-neural-networks-deep-learning-0414>

Mission planner overview¶. (n.d.). Retrieved November 11, 2022, from <https://ardupilot.org/planner/docs/mission-planner-overview.html>

TensorFlow, 2022. https://www.tensorflow.org/tutorials/structured_data/time_series
Six sigma digest template - lean sigma corporation. (n.d.). . Retrieved November 12, 2022, from <https://www.leansigmacorporation.com/support-files/Overview-of-Six-Sigma.pdf>

Six sigma. (n.d.). *International Six Sigma Institute*. Retrieved November 12, 2022, from https://www.sixsigma-institute.org/What_Is_Sigma_And_Why_Is_It_Six_Sigma.php

LOGEMENT, M. D. L. D. T. E. D., 2001. URL <https://libraryonline.erau.edu/online-full-text/ntsb/miscellaneous-reports/MR-f-sc00725ae2.pdf>.

The University of Tennessee, 2022. *Traveling waves*. Retrieved November 12, 2022, from http://labman.phys.utk.edu/phys221core/modules/m11/traveling_waves.html

A mechanical wave is a wave that travels through matter. (n.d.). *bfxs.sgit*. Retrieved November 12, 2022, from <https://bfxs.sgit-university.de/a-mechanical-wave-is-a-wave-that-travels-through-matter.html>

Wikipedia, 2022. Unmanned Aerial Vehicle, Wikimedia Foundation. Retrieved November 12, 2022, from https://en.wikipedia.org/wiki/Unmanned_aerial_vehicle.

High and low standard deviation curves. Source: University of North Carolina, 2012. https://www.nlm.nih.gov/nichsr/stats_tutorial/section2/mod8_sd.html.

Neil Gershenfeld, 2020. <https://fab.cba.mit.edu/classes/MAS.864/>

Thomas Dietterich, 2018. <https://www.microsoft.com/en-us/research/video/anomaly-detection-algorithms-explanations-applications/>

J. Pieniazek and P. Ciecinski, "Temperature and Nonlinearity Compensation of Pressure Sensor With Common Sensors Response," in *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 4, pp. 1284-1293, April 2020, doi: 10.1109/TIM.2019.2910922.

NASA, 2020. <https://ntrs.nasa.gov/citations/20205010768>.

U. Yokkampon, S. Chumkamon, A. Mowshowitz and E. Hayashi, "Anomaly Detection using Variational Autoencoder with Spectrum Analysis for Time Series Data," 2020 Joint 9th International Conference on Informatics, Electronics & Vision (ICIEV) and 2020 4th International Conference on Imaging, Vision & Pattern Recognition (icIVPR), 2020, pp. 1-6, doi: 10.1109/ICIEVicIVPR48672.2020.9306570.

Linsey Retcofsky, 2021. <https://www.uta.edu/news/news-releases/2021/04/08/safer-drone-batteries>

David Morin, 2022. https://scholar.harvard.edu/files/david-morin/files/waves_electromagnetic.pdf

DeepAI, 2022, <https://deepai.org/machine-learning-glossary-and-terms/fourier-transform>

GeekforGeeks, 2022. <https://www.geeksforgeeks.org/difference-between-batch-gradient-descent-and-stochastic-gradient-descent/>

Farhan Rana, 2022. *Home*. Retrieved November 13, 2022, from <https://courses.cit.cornell.edu/ece4060/>

Caramanis et al, 2012. Lecture 4 | september 11 4.1 gradient descent - manning college of ... (n.d.). . Retrieved November 13, 2022, from <https://people.cs.umass.edu/~barna/2015-BigData/conv2.pdf>

Khan Academy, 2022. <https://www.khanacademy.org/science/physics/mechanical-waves-and-sound>

OxfordLanguages, 2022. <https://languages.oup.com/google-dictionary-en/>

Duke University, 2018. https://webhome.phy.duke.edu/~lee/P142/Ref_Waves.pdf

Leaflet, 2022. <https://leafletjs.com/index.html>

Carlos Aguayo, 2020. <https://towardsdatascience.com/deploying-a-simple-machine-learning-model-into-a-webapp-using-tensorflow-js-3609c297fb04>
Agave Cluster, 2022. <https://cores.research.asu.edu/research-computing/user-guide>

Bekdash, O., & la Cour-Harbo, A. (2020). Vibration Analysis for Anomaly Detection in Unmanned Aircraft. *Annual Conference of the PHM Society*, 12(1), 10. <https://doi.org/10.36001/phmconf.2020.v12i1.1143>

Jason Brownlee, 2020. <https://machinelearningmastery.com/multivariate-time-series-forecasting-lstms-keras/>

Caner Dabakoglu, 2019. <https://medium.com/@cdabakoglu/time-series-forecasting-arima-lstm-prophet-with-python-e73a750a9887>

Andriy Danylov, 2022. https://faculty.uml.edu/Andriy_Danylov/Teaching/documents/FormulaSheetFinalexam_001.pdf

Swarthmore University, 2005. <https://lpsa.swarthmore.edu/ZXform/FwdZXform/FwdZXform.html>

Berkeley University, 2015. https://e3s-center.berkeley.edu/wp-content/uploads/2017/08/RET_CStanton-2015.pdf

Niklas Christoffer Petersen, 2019. <https://arxiv.org/pdf/1903.02791.pdf>

Fang, Q., Y. Zhong, C. Xie, H. Zhang and S. Li, 2020. “Research on pca-lstm-based short-term load forecasting method”, IOP Conference Series: Earth and Environmental Science 495, 1, 012015..

Fitzpatrick, R., 2016. URL <https://farside.ph.utexas.edu/teaching/sm1/Thermalhtml/node141.html>.

Spirkovska, L., N. A. R. C. for more papers by this author, D. Iverson, D. Hall, S. G. Technologies, W. Taylor, A. Patterson-Hine, B. Brown, B. Ferrell, N. K. S. C. for more papers by this author and et al., “Anomaly detection for next-generation space launch ground operations”, URL <https://arc.aiaa.org/doi/10.2514/6.2010-2182>. Renotte, N. (2021), URL <https://www.youtube.com/watch?v=mgX0Iz4q0bE>. Rose, J. L. and L. E. Soley, “Ultrasonic guided waves for anomaly detection in aircraft components”, URL <https://pennstate.pure.elsevier.com/en/publications/Ultrasonic-guided-waves-for-anomaly-detection-in-aircraft-compone> (2000).

Foundation, O., 2022. “Different types of similarity measurements”, URL <https://iq.opengenus.org/similarity-measurements/> .

GP;, C. Q. K., 2011. “All dielectric macroscopic cloaks for hiding objects and creat-ing illusions at visible frequencies”, URL <https://pubmed.ncbi.nlm.nih.gov/22109202/> .

Helveston, J. P., 2019. URL <https://p4a.seas.gwu.edu/2019-Fall/challengerExplosion.html>.

Nave, C. R., 1999. URL <http://hyperphysics.phy-astr.gsu.edu/hbase/Waves/standw.html>.

Niklascp, 2018. “Bus-arrival-convlstm/jupyter at master · niklascp/bus-arrival-convlstm”, URL <https://github.com/niklascp/bus-arrival-convlstm/tree/master/jupyter>.

Albert Einstein, 1905. Does the inertia of a body depend upon its energy-content? - fourmilab. (n.d.). . Retrieved November 13, 2022, from https://www.fourmilab.ch/etexts/einstein/E_mc2/e_mc2.pdf

Sbaidrissiyousséf. (n.d.). SBAIIDRISSIYOUSSEF/quantum-papers: I share with you a range of quantum physics papers I've accumulated during years. maybe it will be useful for you. *GitHub*. Retrieved November 13, 2022, from <https://github.com/sbaidrissiyousséf/Quantum-Papers>

Schrödinger, E. (1926, December 1). An undulatory theory of the mechanics of atoms and molecules. *Physical Review Journals Archive*. American Physical Society. Retrieved November 13, 2022, from <https://journals.aps.org/pr/abstract/10.1103/PhysRev.28.1049>

Valkov, V., 2019. URL <https://curiously.com/posts/demand-prediction-with-lstms-using-tensorflow-2-and-keras-in-python/>.

Yang, D., 2019. URL <https://yangdanny97.github.io/blog/2019/03/01/D3-Spider-Chart>.

Salmela, L., N. Tsipinakis, A. Foi, C. Billet, J. M. Dudley and G. Genty, 2021. “Predicting ultrafast nonlinear dynamics in fibre optics with a recurrent neural network”, *Nature Machine Intelligence* 3, 4, 344–354.

interweb jill, 2022. URL <https://bl.ocks.org/interwebjill/8122dd08da9facf8c6ef6676be7da03f>.
Kodjo, E., “Data processing with tensorflow.js”, URL <https://medium.com/@edoh.dev/data-processing-with-tensorflow-js-b42175e0e86e> (2020).
Stoecklin, M., 2005. URL https://faculty.kfupm.edu.sa/ee/samara/transform_pairs.pdf.
Trewavas, A., 2003. “Aspects of plant intelligence”, URL <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4243628/>.

Parrot-Developers, 2016. URL <https://erlerobotics.gitbooks.io/erle-robotics-mav-tools-free/content/en/tools/mavlogdump.html>.

npmjs, 2018. URL <https://www.npmjs.com/package/pca-js>.
TensorFlow, 2020. URL <https://www.tensorflow.org/js/tutorials/setup>.

Public Library of Science, 2018. “Plants can use underground communication to find out when neighbors are stressed”, URL <https://phys.org/news/2018-05-underground-neighbors-stressed.html>.

Constatine M. Tarawneh, 2012. URL <https://faculty.utrgv.edu/constantine.tarawneh/Heat%20Transfer/HeatTransferBooklet.pdf> (2012).

mapbox, 2022. URL <https://www.mapbox.com/static-maps> (2022).

LocationIQ, 2013. URL <https://locationiq.com/>.

Zevross, 2014. URL <http://zevross.com/blog/2014/09/30/use-the-amazing-d3-library-to-animate-a-path-on-a-leaflet-map/>.

Israel might use armed drones in West Bank Counter Terrorism Operations. (n.d.). *The Jerusalem Post* | *JPost.com*. Retrieved November 13, 2022, from <https://www.jpost.com/arab-israeli-conflict/article-716527>

Pilot Institute. (2022, January 26). No drone zones: Where is drone use prohibited? *Pilot Institute*. Retrieved November 13, 2022, from <https://pilotinstitute.com/no-drone-zones/>

Verdict media limited. (n.d.). *Homelandsecurity Technology*. Retrieved November 13, 2022, from <https://www.homelandsecurity-technology.com/projects/s4-ehecatl-unmanned-aerial-vehicle/>

Kůrková, V. (2003, March 5). Kolmogorov's theorem and Multilayer Neural Networks. *Neural Networks*. Pergamon. Retrieved November 14, 2022, from <https://www.sciencedirect.com/science/article/pii/0893608092900128>

Kůrková, V. (2003, March 5). Kolmogorov's theorem and Multilayer Neural Networks. *Neural Networks*. Pergamon. Retrieved November 14, 2022, from <https://www.sciencedirect.com/science/article/pii/0893608092900128>

NLAB String Theory FAQ. (n.d.). *string theory FAQ in nLab*. Retrieved November 17, 2022, from <https://ncatlab.org/nlab/show/string+theory+FAQ>

Bland-Hawthorn, J., Sellars, M., & Bartholomew, J. (2021, March 13). Quantum memories and the double-slit experiment: Implications for astronomical interferometry. *arXiv.org*. Retrieved November 17, 2022, from <https://arxiv.org/abs/2103.07590>