

Satellite Management Agent

by

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Declaration

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Date: September 1, 2022

Abstract

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Opsomming

Skryf jou Afrikaanse opsomming hier.

Acknowledgements

The author wishes to acknowledge the following people and institutions for their various contributions towards the completion of this work:

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Glossary

Something Description of that something.

Something Description of that something.

Something Description of that something.

List of Reserved Symbols

Symbols in this thesis conform to the following font conventions:	
A	Symbol denoting a some general thing (Roman capitals)
\mathcal{A}	Symbol denoting a some general thing (Calligraphic capitals)

Symbol	Meaning
\times	Symbol used to denote the multiplication operator
\times	Symbol used to denote the multiplication operator
\times	Symbol used to denote the multiplication operator
\times	Symbol used to denote the multiplication operator
\times	Symbol used to denote the multiplication operator

List of Acronyms

ADCS: Attitude Determination and Control System

SGP4: Simplified General Perturbations 4

UAV: Unmanned Aerial Vehicle

EFC: Earth Fixed Coordinate

EIC: Earth Inertial Coordinate

ORC: Orbit-referenced Coordinate

SBC: Satellite Body Coordinate

SPCC: Squared Pearson Correlation Coefficient

BST: Binary Search Tree

IGRF: International Geomagnetic Reference Field

FDIR: Fault Detection, Isolation and Recovery

DCM: Direction Cosine Matrix

FDIR: What It Stands For

FDIR: What It Stands For

FDIR: What It Stands For

FDIR: What It Stands For

FDIR: What It Stands For

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CHAPTER 1

Introduction

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The current trend in industry is to create systems that operate autonomously. There is also a trend seen where multi-agent systems with hundred and thousands of sub-systems work within a larger system. Even though each sub-system can operate independently, the health of the network/system is dependent on each agent within the system operating as desired. Consequently, autonomous systems must be able to detect faults within the system. To attain this, a fault detection, isolation and recovery system is required for each individual agent and the system as a whole.

1.1 Background

All systems have the inevitable problem that they will fail. Determining this failure is of a variety of importance for multiple systems. The current tendency is that many systems are more and more integrated. A web of self-driving cars, UAV's for delivery, satellite constellations and more. The problem with any of these systems is if any part of the system is faulty it can have detrimental consequences for a part of the system or the entire system.

Software developers make mistakes, as all humans do. The current industry standard for number of bugs per thousand lines of code is 5 bugs/KLOC at \$5 per line of code. NASA works on 0.004 bugs/KLOC at \$805 per line of code. Imagine having hundreds of thousands of lines of code and having that same code on thousands of satellites. Each fault detection must usually be checked with if statements and logic. This leads to more lines of code and mistakes on trying to capture mistakes. I propose a solution to this problem by using statistical models and machine learning to use satellites in close proximity to determine the health of the other nearby components within the system.

1.2 Informal problem description

<https://www.theverge.com/2020/1/14/21043229/spacex-starlink-satellite-mega-constellation-concerns-astronomy-space-traffic>

The most detrimental effect could be on satellite constellations. Satellites are expensive, \$500000 each for Starlink satellite. And this is also based on the mass production of satellites. Satellites cannot merely be accessed and fixed as other systems. Therefore satellites are used as the specific system for FDIR of systems.

The current situation with cubesats is that ground stations will not be able to keep up with the fault detection and diagnosis of cubesats within constellations where thousands of cubesats are within the same height above the earth. As is the current situation with Starlink.

Kessler syndrome is the effect of one satellite, that is unable to control its orientation and position, causing a collision in orbit. This leads to more debris in the orbit and more collisions and this is detrimental if considered in view of Starlink's mega-constellation.

1.3 Research hypothesis

I propose a fault detection system for each individual satellite and the constellation as a whole. The satellite will have an on-board FDIR system that also uses the information of the satellites closest to its position to provide feedback of its own "health" and the health of the other satellites in its orbit. If a satellite is determined "unhealthy" by all the nearby satellites then the satellite will go into safe mode until the ground station can determine the problem with current satellite.

1.4 Scope and objectives

The following objectives will be pursued in this project/thesis/dissertation:

- I To *conduct* a thorough survey of the literature related to:
 - (a) facility location problems in general,
 - (b) models for the placement of a network of radio transmitters in particular,
 - (c) the nature of parameters required to describe effective radio transmission, and
 - (d) terrain elevation data required to generate an instance of the bi-objective radio transmitter location problem described in the previous section.
- II To *establish* a suitable framework for evaluating the effectiveness of a given set of placement locations for a network of radio transmitters in respect of its total area coverage and its mutual area coverage.
- III To *formulate* a bi-objective facility location model suitable as a basis for decision support in respect of the location of a network of radio transmitters with a view to identify high-quality trade-offs between maximising total coverage area and maximising mutual coverage area. The model should take as input the parameters and data identified in Objective I(c)–(d) and function within the context of the framework of Objective II.

- IV To *design* a generic *decision support system* (DSS) capable of suggesting high-quality trade-off locations for user-specified instances of the bi-objective radio transmitter location problem described in the previous section. This DSS should incorporate the location model of Objective III.
- V To *implement* a concept demonstrator of the DSS of Objective IV in an applicable software platform. This DSS should be flexible in the sense of being able to take as input an instance of the bi-objective radio transmitter location problem described in the previous section via user-specification of the parameters and data of Objectives I(c)–(d) and produce as output a set of high-quality trade-off transmitter locations for that instance.
- VI To *verify* and validate the implementation of Objective V according to generally accepted modelling guidelines.
- VII To *apply* the concept demonstrator of Objective V to a special case study involving realistic radio transmission parameters and real elevation data for a specified portion of terrain.
- VIII To *evaluate* the effectiveness of the DSS and associated concept demonstrator of Objectives IV–VI in terms of its capability to identify a set of high-quality trade-off solutions for a network of radio transmitter locations.
- IX To *recommend* sensible follow-up work related to the work in this project which may be pursued in future.

1.5 Research methodology

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1.6 Project/thesis/dissertation organisation

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CHAPTER 2

Literature Study

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The implementation of FDIR on satellites have multiple complications with regards to the type of data generated by a satellite and the methodologies that can be implemented within the time and memory constraint of a cube-sat processor.

2.1 Anomaly Detection on Satellites

Various methodologies have been tested on different component of satellites. Therefore a summary of these research articles are provided in this section.

2.1.1 Analysis and Prediction of Satellite Anomalies

Wintoft, Lundstedt, Eliasson, and Kalla [37]

2.1.2 Agent-based algorithm for fault detection and recovery of gyroscope's drift in small satellite missions

To ensure that the ADCS of satellites are autonomous every aspect of the control must be able to recover from faults. Carvajal-Godinez, Guo, and Gill [5] developed an algorithm to evaluate the control of a gyroscope and detect whether drifting exists. If drifting is detected another algorithm is deployed to ensure the recovery of the gyroscope drift by updating the error state vector.

2.1.3 Multivariate Anomaly Detection in Discrete and Continuous Telemetry Signals Using a Sparse Decomposition in a Dictionary

[26]

2.1.4 Fault isolation of reaction wheels onboard three-axis controlled in-orbit satellite using ensemble machine learning

[28]

2.1.5 Fault tolerant control for satellites with four reaction wheels

[23]

2.1.6 Innovative Fault Detection, Isolation and Recovery Strategies On-Board Spacecraft: State of the Art and Research Challenges

[36]

2.1.7 Machine learning methods for spacecraft telemetry mining

[19]

2.1.8 Machine learning techniques for satellite fault diagnosis

[20]

2.2 Statistical Methods

2.2.1 Pearson Correlation

Vectors of certain sensors are highly correlated. For instance the vector of the earth sensor is highly correlated since the magnitude of the vector remains more or less constant. To detect anomalies the correlation of vectors can be measured and with a specified threshold the correlation can be indicated as a anomaly or nor.

The squared Pearson correlation coefficient (SPCC) for vectors depicted as

$$\begin{aligned} a &= [a_1, a_2, \dots, a_L]^T, \\ b &= [b_1, b_2, \dots, b_L]^T, \end{aligned}$$

is defined as [3]

$$\rho^2(a, b) = \frac{E^2(a, b)}{E(a^T a)E(b^T b)}. \quad (2.1)$$

The correlation coefficient is proven to be constraint as

$$0 \leq \rho \leq 1, \quad (2.2)$$

where $\rho = 1$ is perfect linear correlation.

2.2.2 Variance

Within a sequential data sample of the satellite, the variance of the variables should be within a given threshold if the satellite is in a stable condition. The variance of the data sample is defined as

$$S^2 = \frac{\sum (x_i + \bar{x})^2}{n - 1} \quad (2.3)$$

where x defines the variable within the dataset.

2.2.3 Kalman-Filter

The Kalman-filter application would require the state-space matrices to be provided in the log file.

2.2.4 Multivariate Guassian Distribution

The assumption that the error of our data is generated with a Guassian distribution with a specific mean, μ , and variance, σ^2 , provides the opportunity for using multi-variate Gaussian distribution to determine the probability of a data-sample within a dataset.

$$\mu_j = \frac{1}{m} \sum_{i=1}^m x_j^{(i)} \quad (2.4)$$

$$\sigma_j^2 = \frac{1}{m} \sum_{i=1}^m (x_j^{(i)} - \mu_j)^2 \quad (2.5)$$

$$p(x) = \prod_{j=1}^n \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left(-\frac{(x_j - \mu_j)^2}{2\sigma_j^2}\right) \quad (2.6)$$

For multi-variate Guassian distribution [14].

$$\sum = \frac{1}{m} \sum_{i=1}^m (x^{(i)} - \mu)(x^{(i)} - \mu)^T \quad (2.7)$$

$$p(x) = \frac{1}{(2\pi)^{\frac{n}{2}} |\sum|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x - \mu)^T \sum^{-1} (x - \mu)\right) \quad (2.8)$$

The Anomalies will be classified based on probabilities smaller than a given threshold $p(x) < \epsilon$.

2.2.5 Kullback-Leibler Divergence

The Kullback-Leibler divergence quantifies the difference between two probability density functions, denoted as $p(x)$ and $q(x)$ [18]. Satellites are systems that are predictable within a time-series. The divergence between two sequential data buffers from the satellite will have a very similar probability distribution. Therefore calculating the difference between two datasets can be used to detect an anomaly based on a given threshold.

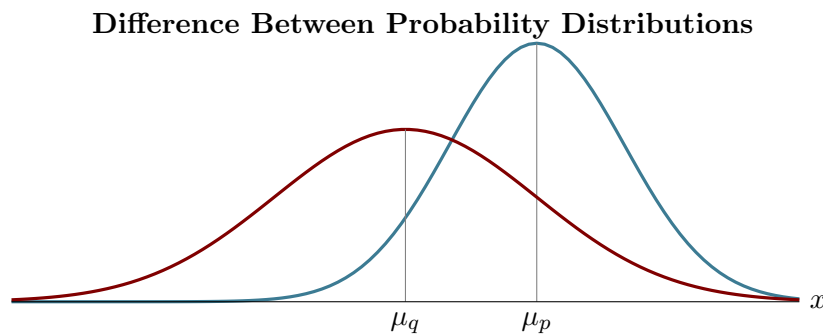
Algorithm 2.1: Multi-variate Guassian Distribution Algorithm**Input** : Data sample from satellite orbit.**Output:** Whether dataset contains anomaly.

```

1 Determine feature vectors  $x_i$ 
2 Determine threshold probabilty,  $\epsilon$ 
3 Calculate  $\mu_j$  with Eq 2.4
4 Calculate  $\sigma_j$  with Eq 2.5
5 Calculate  $p(x)$  with Eq 2.6
6 if  $p(x) < \epsilon$  then
7   | Anomaly = True
8 else
9   | Anomaly = False

```

The difference between the probability distributions from datasets, a and b , in Figure 2.1 cannot simply be calculated as the difference in the mean or the difference in the variance. To overcome this, the divergence between the two distributions can be calculated. Intuitively a point x with a high probability in the dataset a should have a high probability in the dataset b if the two datasets have a small divergence.

FIGURE 2.1: *Guassian Distributions*

The divergence can be expressed as

$$KL(P||Q) = \int p(x) \log \left(\frac{q(x)}{p(x)} \right) dx. \quad (2.9)$$

2.2.6 Canonical Correlation Analysis

Due to the orbital nature of satellites there exist a correlation between various sensors. For instance the sun sensor, magnetometer and earth sensor are correlated based on the desired orientation and orbit of the satellite. This correlation might not be of linear nature, but with non-linear correlation methods such as kernel canonical correlation the correlation can be measured.

However, canonical correlation provides the measure of correlation between a multi-dimensional variable with another multi-dimensional variable. Although this seems profitable for satellite fault detection, it will only be applicable for each the comparison between individual sensors. This will indicate the non-linear correlation of the sun sensor with regards to the magnetometer. The problem however, according to Chen, Ding, Peng, Yang, and Gui [8] is to, determine the

appropriate threshold for which to classify a fault. Chen, Ding, Peng, Yang, and Gui [8] proposed a method for determining the appropriate threshold on page 5, algorithm 1. [15] [38]

Python - Pyrrca package

K-means-based

Guassian Mixture Model

Just-In-Time-Learning

[9]

2.3 Feature Extraction

To <https://towardsdatascience.com/feature-extraction-techniques-d619b56e31be>

2.3.1 Prony's Method

2.3.2 Convolutional Networks

2.3.3 K-means Clustering

K-clustering: Clustering multiple points with similar features.

2.3.4 Principal Component Analysis

[11] [13]

2.3.5 Partial Least Square

2.3.6 Independent Component Analysis

2.3.7 Locally Linear Embedding

2.3.8 Linear Discriminant Analysis

2.3.9 Autoencoder

2.3.10 t-Distributed Stochastic Neighbor Embedding

2.4 Supervised Learning

Supervised learning consists of models that are trained on labelled data. This is not a problem with simulation, but with the real data, it is a problem and to provide tests on the real data to label it must be proficient. If unsupervised learning and statistical methods are not sufficient in their accuracy, a method for labelling the real data must be provided.

2.4.1 Random Forests

[30, 25, 27]

2.4.2 Long Short Term Memory

Time-series data: LSTM or DLSTM

2.4.3 Support Vector Machines

Support Vector Machines

2.4.4 Naive Bayes

Naive Bayes

2.4.5 K-nearest neighbours

K-nearest neighbours

2.4.6 Artificial Neural Networks

Artificial Neural Networks

2.5 Unsupervised Learning

Density-based, distance, Clustering

2.5.1 Isolation Forests

This unsupervised learning methods is based on the principle of isolating data points by slicing the data with random conditions [34]. The data is randomly split into specified sample sizes with a randomly selected dimension and a randomly selected cut-off value. For each sample size the data must be split until each data point within the sample is isolated from all other data points. Training of a single tree is completed when all the data points are isolated and this training must be repeated for all the data samples, however many are predefined.

The distance measured from the first split the *tree top* to the isolated data point is used to determine whether a data point is anomalous or not [17]. The logical reasoning for support of this algorithm is that data points which are non-anomalous will be more closely related and hence have more splits to separate the data points until isolation is achieved. Therefore, the distance from the tree top for non-anomalous data points will be longer than anomalous data points which will have a shorter distance from the tree top. Therefore non-anomalous data points are closer to the *root*.

Figure 2.2 demonstrates the splitting of the data points until isolated. Each split or *branch* only splits the data into two groups. After training multiple trees, a single data point is "sent through

the forest” and the distance from the tree top for each tree is calculated and the average of all the trees are used to calculate the average distance for the data point. Using a threshold for the distance, the data point is classified as anomalous or not.

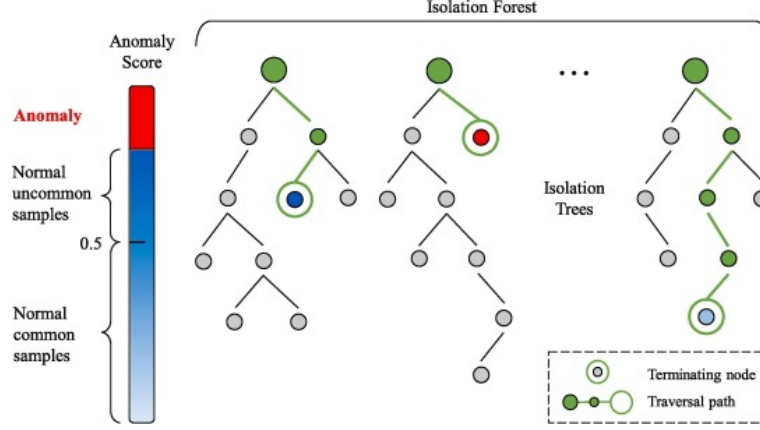


FIGURE 2.2: Isolation Forests [6]

The anomaly score is calculated with Eq 2.10

$$s(x, n) = 2^{-E(h(x))/c(n)} \quad (2.10)$$

where $E(h(x))$ is the average value of the distance measured from the tree top for a single data point in all the trees [17] and n is the size of a data sample used to train a single tree. For the distance to be normalized, $c(n)$ — the mean distance from the tree top in an unsuccessful search in a *Binary Search Tree* (BST) — is used and is calculated as

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n}. \quad (2.11)$$

$H(i)$ in Eq 2.11 is the harmonic number and is estimated with Euler’s constant as

$$H(i) \approx \ln(i) + 0.5772156649. \quad (2.12)$$

Isolation Forests, however have multiple issues, since it splits data in rectangles as seen in Figure 2.3(a). This is due to the slicing algorithm selecting a feature, x and a cut-off value, v . Consequently, the data is either split vertically or horizontally — if seen as a two dimensional dataset. This split method is unable to categorise complex data structures. These issues however are addressed by Hariri, Kind, and Brunner [17] and led to the *Extended Isolation Forest* algorithm.

The extended isolation forest algorithm generalises the isolation forest algorithm by applying a slope to each slice. Data points are therefore divided into two groups depending on the “side” of the plane or slice as seen in Figure 2.3(b).

It is evident that applying an angle of 0° to all the slices the general algorithm of the extended isolation forest produces the standard isolation forest algorithm where planes or slices are perpendicular to the axis of the randomly selected feature, x .

2.5.2 Local Outlier Factor

Most algorithms for anomaly detection are based on a metric which accounts for the entire dataset [4]. However, many anomalies are identifiable in relation to the local neighbourhood

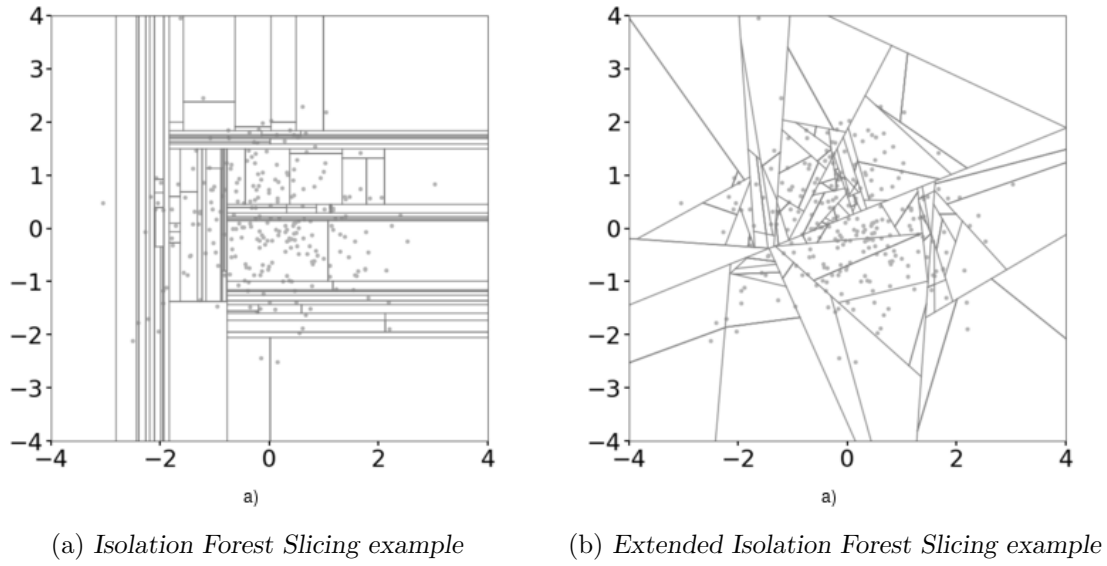
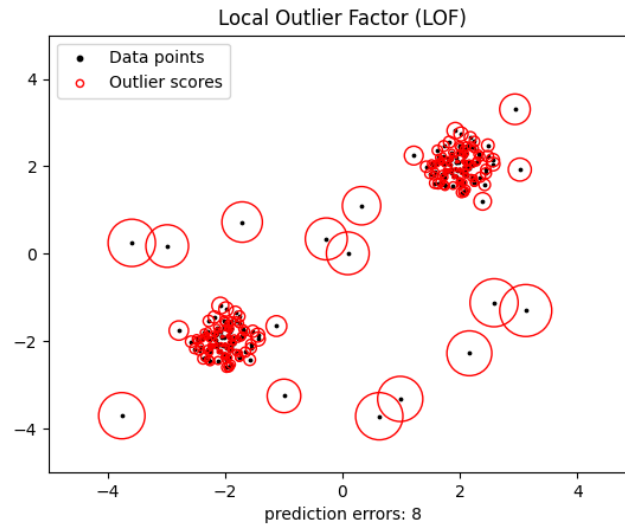


FIGURE 2.3: The slicing of Isolation Forest vs Extended Isolation Forest

of data points and not the overall dataset. Therefore, Breunig, Kriegel, Ng, and Sander [4] developed the local outlier factor *LOF* algorithm that provides a measure of a data point's "outlierness". This implies that a data point is not classified as an anomaly or not, but a local outlier factor is calculated to determine how much a data point is distantiated from it's k -nearest neighbours. This is clearly demonstrated in Figure 2.4 where the data points which are clustered together have smaller LOF's than data points which are removed from the highly dense areas.

FIGURE 2.4: *LOF* measure

To calculate the LOF, the k -distance must be calculated and also the local reachability density *lrd*. The k -distance, is the k^{th} ranked $distance(o, p_i)$. Where $distance(o, p_i)$ is the distance between data point o and any data point p_i , with $i \in N$, where N is the number of data points within the dataset with a minimum value of $MinPts$. To reduce fluctuations in the

$distance(o, p_i)$ the distance between o and p_i is replaced with

$$\max\{distance(o, p_i), k\text{-distance}\} \quad (2.13)$$

and will henceforth be referred to as the reachability distance [4]. The lrd of a data point, p , is calculated as

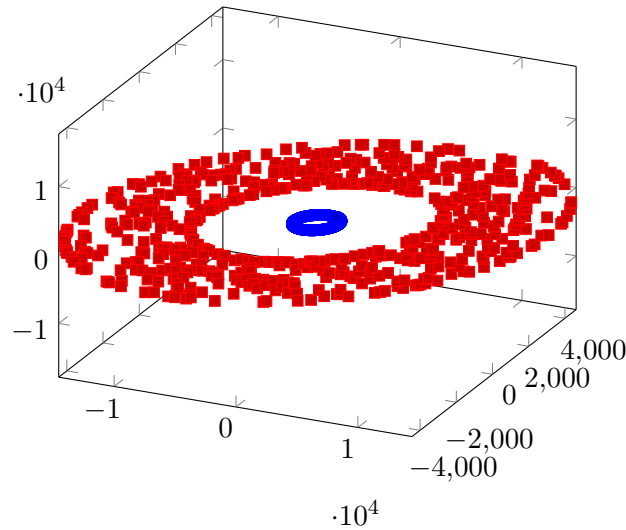
$$lrd_{MinPts}(p) = 1 / \left(\frac{\sum_{o \in N_{MinPts}(p)} reachdist_{MinPts}(p, o)}{|N_{MinPts}(p)|} \right) \quad (2.14)$$

and denotes "the inverse of the average reachability distance based on the $MinPts$ -nearest neighbours of the p " — Breunig, Kriegel, Ng, and Sander [4]. Eq 2.14 enables the calculation for the LOF of point p as shown in Eq 2.15

$$LOF_{MinPts}(p) = \frac{\sum_{o \in N_{MinPts}(p)} \frac{lrd_{MinPts}(o)}{lrd_{MinPts}(p)}}{|N_{MinPts}(p)|} \quad (2.15)$$

The rule of thumb for detecting an outlier is that when the LOF is larger than 1, then the point is considered an outlier with respect to its neighbourhood. This however is not fixed and the threshold can be changed depending on the application. This method is aimed at producing a measure of the "outlierness" of a data point within a local neighbourhood and not for all the data points. This method will thus be implemented for the satellite anomaly detection, since it will detect anomalies within the two neighbourhoods produced by the eclipse during orbit. This method will also be able to detect measurements of earth sensors, sun sensors and magnetometers that drastically change from the previous orbital data. For example in Fig ?? it is evident that the LOF will be comparatively larger for the red data points, which are anomalies, to the blue data points that are the normal orbit of the satellite.

Earth Sensor During Multiple Orbits



2.5.3 Kernel Adaptive Density-based

Kernel adaptive density-based: Is an algorithm that uses the density factor of a data point relative to other data points to determine whether the data point is an outlier or not.

2.5.4 Loda

Loda: Is a fast and efficient anomaly detection algorithm that used histograms to evaluate data points to determine whether a data point is an outlier. Loda is an on-line method and not a batch method.

2.5.5 Robust-kernel Density Estimation

Robust-kernel density estimation

2.6 Reinforcement Learning

Active Anomaly detection with meta-policy (Meta-AAD) is a deep reinforcement learning approach that is based on the actor-critic model. The agent must query data points within the given dataset (where the queried point is the data top 1 data point). The query is given to a human

2.7 Summary

CHAPTER 3

Simulation

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To implement and research various FDIR systems on satellites an simulation of satellite dynamics and kinematics is developed. The focus of this thesis is on small satellites and more specifically cubesats. For the simulation of the ADCS of the satellite [2, 22, 24] were referenced during the development of the satellite simulation. The simulation was developed in Python to simulate the dynamics and kinematics during a satellite orbit. The faults for the subsystems are also developed within the simulation and will be discussed within this chapter.

3.1 Attitude Determination and Control System

For the mission of the specific satellite in this document the main operational goal of the Attitude Determination and Control System (ADCS) on this specific satellite mission is to control the payload to point towards the centre of the earth.

3.1.1 Coordinate Frames

The coordinate frames in aerospace is a fundamental part of the ADCS. To determine the orientation and position of an object, it should be relative to a fixed frame. Consequently, the Earth inertial coordinate (EIC) frame is the fixed frame from which every other frame is relative to.

A coordinate frame consists of three orthogonal vectors which is commonly referred to as x, y, and z. The axis of the coordinate frame is appropriately named as X-axis, Y-axis and Z-axis as seen in Figure... A vector (\vec{r}) within the current coordinate frame can thus be expressed as

$$\vec{r} = x\vec{i} + y\vec{j} + z\vec{k} \quad (3.1)$$

where the magnitude of \vec{r} is denoted as $|\vec{r}|$ and is equal to

$$|\vec{r}| = \sqrt{x^2 + y^2 + z^2}. \quad (3.2)$$

The Earth-centered coordinate frames are divided into two, namely the EIC and earth fixed coordinate (EFC) frame. EFC is fixed to the earth and rotates with it. This frame is important with respect to where the satellite position is with regards to position's on earth, such as the ground station. It is also important for the modelling of the geomagnetic fields.

The EIC is defined as the Z-axis pointing towards the north pole, the X-axis pointing towards the Vernal Equinox, Υ , and the Y-axis completing the orthogonal set. The EFC is a copy of the EIC, with the Z-axis being identical, however the EFC rotates with the earth. The EFC in relation to the EIC can be expressed by a single angle of rotation, which is the Greenwich Hour Angle (GHA), α_G . With the knowledge of t — the elapsed time since t_0 , w_E — the angular rate of the earth, and $\alpha_{G,0}$ — the GHA at $t = t_0$, α_G can be calculated as

$$\alpha_G = w_E t + \alpha_{G,0} \quad (3.3)$$

To transform a vector from one coordinate frame to another, a transformation matrix, \mathbf{A} , is required. For example vector \vec{r}_{EFC} can be transformed to \vec{r}_{EIC} with

$$\vec{r}_{EIC} = \mathbf{A}_{EFC}^{EIC} \vec{r}_{EFC} \quad (3.4)$$

with \mathbf{A}_{EFC}^{EIC} being the EFC-to-EIC transformation matrix. Due to the definition of both coordinate frames, \mathbf{A}_{EFC}^{EIC} can be defined .

$$\mathbf{A}_{EFC}^{EIC} = \begin{bmatrix} \cos(\alpha_G) & -\sin(\alpha_G) & 0 \\ \sin(\alpha_G) & \cos(\alpha_G) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3.5)$$

To determine the satellite position, satellite coordinate frames must be used. Three satellite-centred coordinate frames are used, namely the inertial-reference coordinate frame (the satellite

does not rotate), the orbit-referenced coordinate (ORC) frame and the satellite body coordinate (SBC) frame. The IRC frame is only acknowledged, since it is the frame that is fixed (as it does not rotate around the centre of the satellite), however it changes position with the orbit of the satellite. This frame is not used to determine the position of the satellite and will not be referenced for the remainder of this document.

The ORC frame changes location as the satellite moves, however the Z-axis is always pointing towards the centre of the earth, with the Y-axis being the anti-normal and the X-axis completing the orthogonal set. To transform a vector from the EIC frame to the ORC frame the unit position vector, \vec{r}_{sat} and the unit velocity vector, \vec{v}_{sat} in EIC [7].

$$\mathbf{A}_{EIC}^{ORC} = [\hat{u} \quad \hat{v} \quad \hat{w}]^T \quad (3.6)$$

where

$$\hat{w} = -\frac{r_{sat}}{\|r_{sat}\|} \quad (3.7)$$

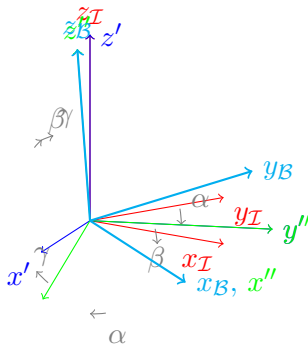
$$\hat{v} = -\frac{r_{sat} \times v_{sat}}{\|r_{sat} \times v_{sat}\|} \quad (3.8)$$

$$\hat{u} = \hat{v} \times \hat{w} \quad (3.9)$$

The SBC frame is the frame fixed to the satellite and it is the relative rotation of the satellite in relation to the ORC. Thus for the mission of this satellite it is required that the SBC and ORC frames coincide. For the transformation of a vector from the ORC to SBC frame, the direct cosine matrix (DCM) also referred to as \mathbf{A} or \mathbf{A}_{ORC}^{SBC} is used. For the remainder of the document the DCM will be referred to as \mathbf{A}_{ORC}^{SBC} to avoid any confusion. The calculation of this transformation matrix will be discussed in §3.1.2.

3.1.2 Attitude

To determine the attitude of an object, a model must be used to determine the rotation of an object in three dimensions. For this the visual and intuitive example of the Euler angles exist. Euler angles are the rotation of an object around three orthogonal axis, that change orientation with the rotation of the object.



Euler angles - gimbal lock

Euler angles and DCM will be acknowledged and explained why they are not applicable. In some literature the first and last quaternion are swapped.

3.1.3 Satellite Kinematics and Dynamics

3.1.4 Rungka-kutta

3.2 Environment

3.2.1 Earth Orbit

Earth orbit according to sgp4 and also the placement of the earth sensor.

Show plot of 3D earth orbit...

3.2.2 Sun

The calculations for the sun position and also the placement of the coarse and fine sun sensor.

Show graph of sun plot...

3.2.3 Geomagnetic field

$$V(r_s, \theta, \lambda) = R_E \sum_{n=1}^k \left(\frac{R_E}{r_s} \right)^{n+1} \sum_{m=0}^n (g_n^m \cos(m\lambda) + h_n^m \sin(m\lambda)) P_n^m(\theta) \quad (3.10)$$

Show graph of geomagnetic plot...

3.3 Sensor models

3.3.1 Position of Sensors and Field of View

3.3.2 Noise

3.4 Disturbance models

3.4.1 Gravity Gradient

3.4.2 Aerodynamic Disturbance

[32]

3.4.3 Wheel Imbalance

3.5 Attitude Determination

In this section discuss the Kalman filter.

3.5.1 Kalman Filter

[35]

3.6 Attitude Control

Magnetic control during detumbling Reaction wheel control during normal operation

3.7 Typical Faults

For the simulation of the satellite and the induced faults to train and test various anomaly detection methodologies a database of typical faults is required. Tafazoli [33] made a study of the percentage of failure per subsystem.

3.7.1 Probability of Fault Occurrence

The occurrence of a fault depends on the reliability of that equipment. Guo, Monas, and Gill [16] studied the reliability of small satellites and calculated the parameters for the Weibull distribution based on real data. To model the probability of a fault to occur the probability density function is used [35].

This probability however is small and for the training of the system the data is too sparse for the computational abilities of any regular PC. Thus the probability of a failure during training is fixed to $1/1000000$ to produce the data required for the anomaly detection with a million test samples.

3.7.2 Set of faults

A set of typical faults for the ADCS is shown in Table ??.

Internal Faults

Internal Faults					
Fault classes	Failure rate per hour	Fault causes	References	Possible effect	Possible permutations
Reaction wheels	2.5E-7 [31]	Reaction wheel electronics fail	[1] [21]	Does not respond to control inputs	Momentum remains the same or decreases slightly due to friction
		Overheated reaction wheel	[37]	Decrease in speed	1% of initial speed per second
		Catastrophic failure (cause unknown)	[10]	Stops rotating	0
		Increase in rotation speed (Unknown cause)	Gerhard Janse van Vuuren	Wheel speed increases	Between 90-100% of maximum wheel speed
Magnetorquers	ADCS fault table8.15E-9 [31]	Polarities are inverted	[12]	Incorrect rotation	
Magnetometers	8.15E-9 [31]	Unknown	Gerhard Janse van Vuuren	Stops reacting	Provides no feedback or the output remains constant
		Magnetometers and magnetorquers interfered with each other	[21]	Noise on magnetometers and noise on control of magnetorquers	Between x3 and x5 times the normal noise magnitude Guassian distribution
		Unknown	[29]	Noisy Earth Sensor effected pointing accuracy	Between x5 and x10 times the normal sensor noise based on Guassian distribution
Earth Sensor	-	Unknown	[12]	Erroneous measurements	Uniform random values
Sun sensor	-	Cross-wired during installation	[21]	Sun sensor fails	output is 0
Star tracker	-	Unknown Shutter on star tracker is closed	[12]	Star tracker fails	output is 0
Overall control	-	Incorrect control law or variation thereof	Gerhard Janse van Vuuren	Angular velocity suddenly increases or decreases or oscillation results	Increase to 75 - 100% Decrease to 0 - 25% Oscillates
Common data transmission errors	-	Sign flip	[12]	Processor-based	Processor outputs and/or inputs experience a sign flip
		Bit flip	N/A		Processor outputs and/or inputs experience a bit flip
		Insertion of zeros	[21]		Processor outputs and/or inputs experience an insertion of a zero
Possible sensors errors	-	Unknown	N/A	High sensor noise	Between x5 and x10 times the normal sensor noise based on Guassian distribution

CHAPTER 4

Implementation of Methods on Actual Satellite

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4.1 Isolation Forests

A trained network will be developed from simulation data or the data generated during the first few orbits of a satellite. Afterwards the anomaly score will be calculated for a data point and based on a given threshold, the data point will be flagged as an anomaly or not.

CHAPTER 5

Conclusion

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5.2	Appraisal of project/thesis/dissertation contributions	26
5.3	Suggestions for future work	26
5.4	What the student has learnt during this project	26

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5.1 Project/thesis/dissertation summary

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5.2 Appraisal of project/thesis/dissertation contributions

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5.3 Suggestions for future work

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5.4 What the student has learnt during this project

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APPENDIX A

Project Timeline

The expected timeline is given in Figure A.1 in Gantt-chart form.

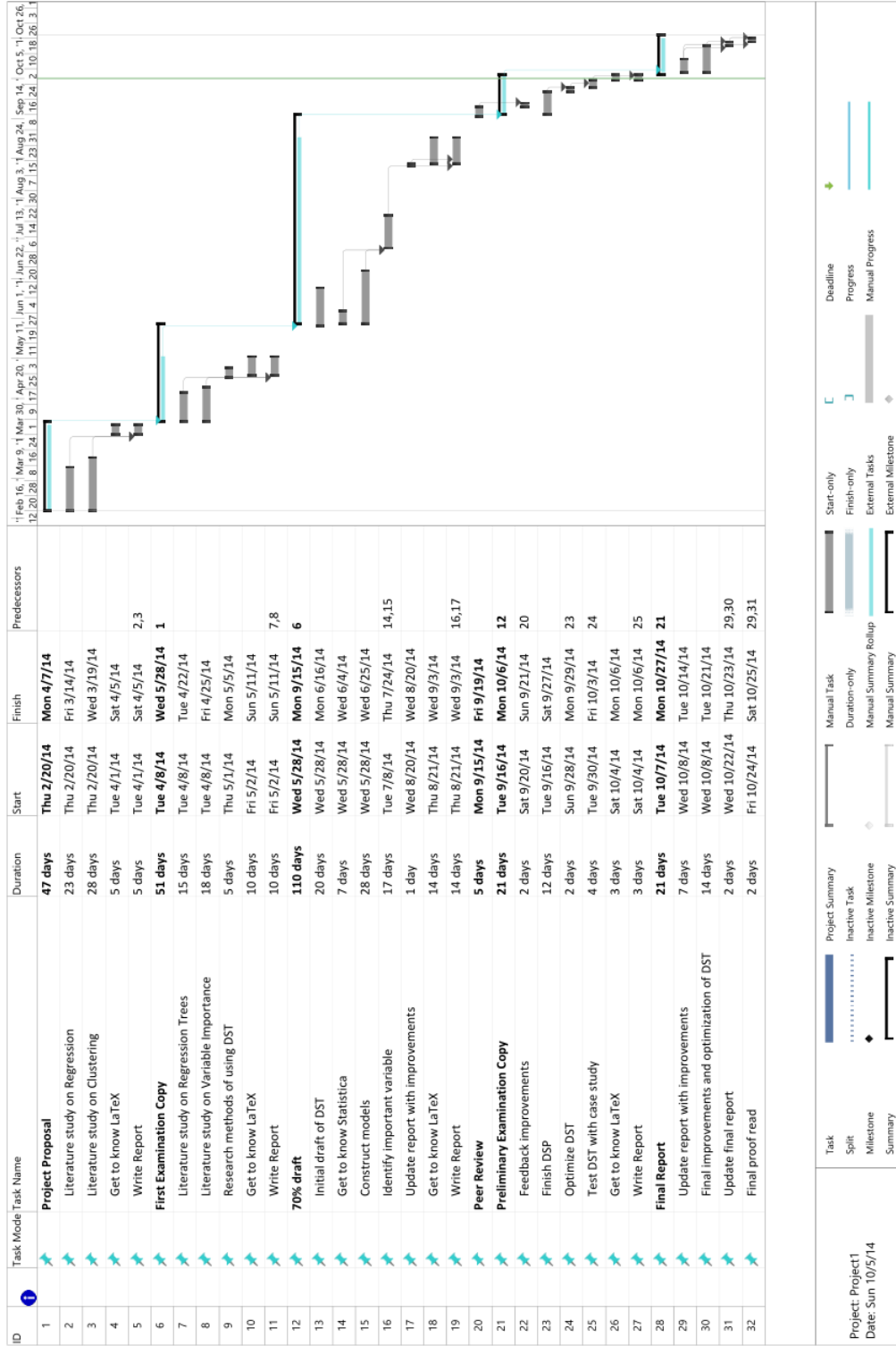


FIGURE A.1: Expected timeline in Gantt-chart form.

APPENDIX B

Data

Data related to the Case Study in Chapter 5 are presented in Table B.1.

		this goes across 6 columns					
		col a	col b	col c	col d	col e	col f
this is sideways, and goes across six rows	row 1						
	row 2						
	row 3						
	row 4						
	row 5						
	row 6						

TABLE B.1: *Type full caption here.*