Health Monitoring System of CubeSats: A Comprehensive Review

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Abstract
CubeSats, miniature satellites with low costs, have gained widespread use recently for various applications such as scientific research, technology demonstrations, and earth observation. The proper functioning of CubeSats requires a reliable health monitoring system. This paper offers a thorough analysis of existing CubeSat health monitoring systems. The outline of the different methods employed, including Telemetry, Onboard Monitoring, model-based, and machine learning approaches are checked. The review summarizes the crucial findings and results of prior studies and highlights the advantages and limitations of each method. Also, the current trends and future prospects for CubeSat health monitoring systems research are discussed to address the key challenges and opportunities for future progress. Moreover, the paper provides insights into the key considerations for implementing CubeSat health monitoring systems in real-world applications. Finally, the paper offers recommendations for future research directions in the field. This paper serves as a comprehensive guide for researchers and professionals in the CubeSat health monitoring field.

Keyword: Cubesat, Health monitoring system, Machine learning, Model based, Reability, Real time monitoring, Fault detection

Introduction

CubeSats, miniaturized and low-cost satellites, have made a significant impact on the space industry in recent years. Their compact design, affordability, and ease of deployment make them a preferred choice for a range of applications, such as scientific research, technology demonstration, and earth observation. The growing number of CubeSats in orbit has necessitated the development of reliable health monitoring systems to guarantee their proper functioning [1].
Health monitoring systems are critical components of CubeSats, providing real-time updates on their status and enabling operators to quickly detect and address any issues. This information is vital for ensuring the longevity and successful completion of CubeSats' missions.
The field of CubeSat health monitoring systems has seen considerable growth, with researchers and practitioners exploring a range of techniques, including model-based and machine learning methods. Despite this, there has been limited research focused exclusively on CubeSat health monitoring systems [1].
This paper presents a comprehensive review of the existing literature on CubeSat health monitoring systems. Our goal is to provide a comprehensive overview of the various approaches used for CubeSat health monitoring and to summarize the key findings and results of prior studies. Additionally, we examine the current trends and future prospects for CubeSat health monitoring systems research, addressing the key challenges and opportunities for future work.
The paper is structured as follows: the next section provides the terminology within the paper. Next section provides a literature review of existing CubeSat health monitoring systems research. Then, the key findings and results of Machine learning and Model-based approaches are summarized to highlight the strengths and weaknesses of each approach. Finally, the trends and future directions for CubeSat health monitoring systems research are presented in conclusions.

Terminology

The following sections give an introduction to the terminology used in this paper.
Autonomy: Autonomy is the capability to make rational, informed, self-determined, and self-reliant decisions. For a system to be called autonomous, it needs to be able to sense, think and act in the world around it. It requires the capability to sense its surroundings and some consciousness about its capabilities and their effects on its environment and internal state. From this knowledge about the world and about itself, an autonomous system

about the world and about itself, an autonomous system can draw conclusions and make decisions concerning its own goals and carry out actions to reach these goals [2].
Artificial Intelligence: For a computer system to be called intelligent, it needs to be able to make rational decisions based on its observations of the world and a set of goals it shall achieve. Despite sounding like a cutting-edge strategy, artificial intelligence (AI) has roots in the 1950s and spans a number of paradigms and techniques. As shown in **Fig. *1***, Machine learning (ML), Deep learning (DL), Reinforcement learning, and their intersections are all components of AI. The overall goal of AI research is to enable directed learning or to make the machine smarter by following specific rules. Here, the term "smarter" refers to the capacity to carry out difficult cognitive activities that would typically need a person, such as classification, regression, clustering, detection, recognition, segmentation, planning, scheduling, or decision-making [3].
Anomaly Detection: Finding patterns in some underlying group of data points and identifying deviations from those patterns are the goals of anomaly detection. This is crucial for spacecraft to detect off-nominal situations and react appropriately. Anomaly detection is done on multi-dimensional data, such as pictures, as well as time-series data, such as temperature readings over time, primarily to identify scientific opportunities or reduce the amount of data chosen for downlink [2].

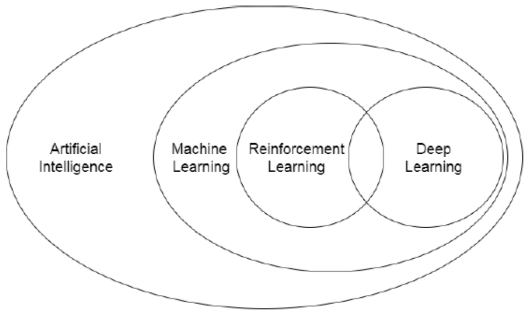

Fig. 1. Artificial Intelligence, Machine Learning, Deep Learning and Reinforcement [4]

CubeSat: A small satellite, typically measuring some centimeters, designed for low-cost space missions and research [5].
Health Monitoring: The process of monitoring the performance and status of a system to ensure it is functioning properly [5].
Model-Based Monitoring: An approach that uses mathematical models to describe the behavior of a system, and uses this information to diagnose and predict issues.[4]
Machine Learning-Based Monitoring: An approach that uses data-driven techniques, such as deep neural networks and decision trees, to detect and diagnose issues in real-time [7].
Sensor Data: Data collected from sensors on a CubeSat, used for health monitoring and system diagnosis [5].
Health Metrics: Quantitative measurements of the performance and status of a CubeSat or subsystems [5].
Real-Time Monitoring: Monitoring the performance and status of a system in real-time, as opposed to after the fact [5].
Diagnosis: The process of identifying the cause of an issue or problem in a system [4].
Failure Modes: The ways in which a system can fail or malfunction, and the consequences of these failures [2].
Redundancy: The use of multiple systems or components to ensure the availability of the overall system, even in the event of failures in individual components [5].
Reliability: The likelihood that a system will function as expected, over an specified period of time [2].

Literature Review

This section summarizes the existing research on CubeSat health monitoring systems and provides an overview of the different approaches and methods used. Then, classifies the existing research into different categories, such as model-based approaches, machine learning approaches, and others, and provides a comparison of the different methods and also introduce some famous companies and researchers that work on this field.
CubeSats are small satellites that have become increasingly popular for various applications in recent years. Health monitoring systems are essential to ensure the proper functioning of CubeSats and to detect any issues before they become critical. There has been a lot of research in this area, and here's an overview of some key findings and developments:

1. Onboard sensors: The utilization of onboard sensors is a crucial aspect in the monitoring of CubeSat health. These sensors collect data regarding various CubeSat parameters including temperature, acceleration, and angular velocity. The obtained data is then analyzed to evaluate the CubeSat's overall health status and identify any abnormal patterns that may suggest an issue.
One of the prime benefits of using onboard sensors is the ability to monitor the CubeSat in real-time. This feature is vital for early detection of problems, before they escalate. Furthermore, the implementation of onboard sensors provides a more holistic view of the CubeSat's health by collecting data on multiple parameters simultaneously. There have been many researchers and companies that have worked on developing onboard sensors for CubeSats [8].
Some of the notable individuals and organizations include:

- Professor Jordi Puig-Suari of California Polytechnic State University, who co-designed the CubeSat specification [9],
- CubeSat Kit, a company that provides complete CubeSat kits, including onboard sensors [10].

In summary, the use of onboard sensors is a vital aspect of CubeSat health monitoring systems. With ongoing research and development efforts, this approach continues to be an important area of focus for CubeSat health monitoring.

2. Predictive maintenance: In the field of CubeSat health monitoring, predictive maintenance has emerged as a valuable technique for predicting and mitigating failures. This approach involves the use of onboard sensors and other data sources to analyze trends and detect anomalies that may indicate a future malfunction. By utilizing predictive maintenance, maintenance and repair schedules can be proactively planned, reducing the risk of unplanned downtime and preventing the escalation of minor issues into serious problems [11].

The application of predictive maintenance in CubeSat health monitoring has a long history of development and innovation. Initially, statistical methods, such as regression analysis, were employed to identify patterns in sensor data that may indicate a potential malfunction. However, with the advent of machine learning algorithms, such as neural networks and decision trees, predictive maintenance has undergone a paradigm shift. These algorithms are capable of analyzing large amounts of data and can be trained to recognize patterns and make predictions, resulting in more accurate and effective maintenance predictions [11].

Some of the most prominent researchers and companies in the field of predictive maintenance for CubeSats include:

- Dr. Panos Antsaklis of the University of Notre Dame, who has developed predictive maintenance algorithms for CubeSats [12],
- Dr. Michael Zavlanos of Duke University, who has worked on developing machine learning algorithms for CubeSat health monitoring [13],
- Nanosatisfi, a company that provides CubeSats and associated services, including predictive maintenance [10].

The predictive maintenance is a critical part of CubeSat health monitoring. It allows for the early detection of problems and reduces the risk of more serious failures. The development of machine learning algorithms has greatly improved the effectiveness of this approach, and it continues to be an active area of research and development.

3. Model-based: The model-based method in CubeSat health monitoring involves constructing mathematical models that simulate the behavior of a CubeSat and its subsystems. These models enable the prediction of the CubeSat's performance and detection of potential issues prior to their manifestation [14].

The implementation of model-based approach in CubeSat health monitoring has a rich legacy, dating back to the inception of space exploration where engineers and scientists devised models to comprehend the behavior of spacecraft and their components. These models were primarily derived from fundamental principles, such as the laws of physics, and utilized to predict the spacecraft's behavior and identify potential problems. Technology advancements have greatly impacted the application of the model-based approach in CubeSat health monitoring. Modern models and simulation tools are significantly more sophisticated, accounting for various factors such as temperature, radiation, and onboard sensor behavior, to predict the CubeSat's behavior and detect potential issues [14].

Some of the most prominent companies in the field of model-based approach for CubeSat health monitoring include Nanosatisfi [10].

The implementation of the model-based approach is essential to the health monitoring of CubeSats. Through the use of mathematical models to represent the behavior of CubeSats and their subsystems, this approach provides the ability to anticipate performance and identify any potential issues beforehand. The new emerging complex models and simulation tools has significantly enhanced the utility of the model-based approach, and it remains a thriving area of research and development.

4. Machine learning: The application of machine learning in CubeSat health monitoring has been a rapidly developing area of research in recent years. The objective of this approach is to create algorithms that can automatically identify anomalies and predict failures, based on the data obtained from onboard sensors and other sources [15].

In the early stages of development, basic algorithms such as decision trees and artificial neural networks were utilized for the analysis of sensor data and detection of anomalies. These algorithms were trained on historical data to discern patterns that suggest a potential problem.

Recently, the advent of more advanced machine learning algorithms such as deep neural networks and reinforcement learning has significantly enhanced the efficiency of this approach. These algorithms have the capability to process vast amounts of data and can be trained to recognize intricate patterns and make predictions based on that data [15].

Prominent researchers and companies in the field of machine learning for CubeSat health monitoring include Dr. Michael Zavlanos [13], Dr. Panos Antsaklis [12], and Nanosatisfi [10].

The machine learning has the potential to greatly improve the ability to detect anomalies and predict failures, reducing the risk of more serious problems in satellites. The development of more advanced machine learning algorithms has greatly improved the effectiveness of this approach, and it continues to be an active area of research and development [15].

5. Wireless communication (Telemetry): Wireless communication is an important aspect of CubeSat health monitoring. It involves sending data from the CubeSat to a ground station using wireless communication systems. The data transmitted includes information from onboard sensors and other sources that are used to monitor the CubeSat's health. Wireless communication for CubeSat health monitoring has a long history, starting from the early days of satellite communication when engineers and scientists developed systems to transmit data from satellites to ground stations. Over the years, these systems have become more reliable, efficient, and capable of transmitting large amounts of data [16].

Recently, wireless communication for CubeSat health monitoring has been transformed by the advancement of more advanced communication systems, such as low Earth orbit (LEO) satellite networks. These networks allow CubeSats to send data in almost real-time, providing essential information for health monitoring and enabling quick responses to potential issues [16].

Some of the most well-known companies in the field of wireless communication for CubeSat health monitoring include:

- Iridium Communications, a company that provides satellite communication services, including for CubeSats [17].
- Nanosatisfi [10].

The wireless communication as an essential aspect of CubeSat health monitoring, enables the transmission of data from CubeSats to ground stations, providing the necessary information for health monitoring and quick response to potential problems. The improvement of advanced communication systems continues to enhance the effectiveness of this approach and remains a subject of ongoing research and development.

6. Fault detection and diagnosis (FDD): The method of Fault Detection and Diagnosis (FDD) has been utilized for monitoring the health of CubeSats and detecting faults within the CubeSat system. The approach focuses on continuously monitoring various parameters and signals within the CubeSat to identify any anomalies or deviations from the expected behavior. In the event of a fault detection, FDD employs data analysis and modeling techniques to diagnose the root cause of the issue. The evolution of FDD within CubeSat health monitoring can be traced back to the initial stages of space systems health monitoring, when engineers and scientists developed techniques for detecting and diagnosing faults. As CubeSats have become more complex over time, FDD has emerged as a crucial aspect of CubeSat health monitoring, with ongoing advancements in technology contributing to its continued significance [2].

As summary, FDD is a crucial component of CubeSat health monitoring. It allows for the detection and diagnosis of faults and problems within the CubeSat system, providing critical information for health monitoring and enabling quick response to potential problems. The development of advanced FDD algorithms and techniques continues to be an active area of research and development, as CubeSats continue to play an increasingly important role in space exploration and other applications [2].

Overally, CubeSat health monitoring systems are an important aspect of CubeSat design and operation. The development of these systems has been driven by the increasing popularity and use of CubeSats, and they play a critical role in ensuring their safe and reliable operation. In the subsequent section of this review, a comprehensive examination of two state-of-the-art methods, Machine learning and Model-based, will be performed, delving deeper into their respective intricacies.

Machine Learning Approch

Machine learning is a rapidly growing field that is being applied to a wide range of problems, including CubeSat health monitoring. This approach utilizes algorithms and models trained on historical data to predict and identify faults in real-time. The following steps outline the process of using machine learning for CubeSat health monitoring [5, 7]:

1. Data Collection: The first step in using machine learning for CubeSat health monitoring is the collection of relevant data. This data should include information related to CubeSat health and performance, such as temperature, voltage, current, and motion readings. This data should be collected over a period of time, to ensure that the machine learning algorithms have enough data to be trained.
2. Data Preprocessing: The collected data must be preprocessed to ensure that it is in the correct format for use with machine learning algorithms. This may include cleaning the data to remove any irrelevant or incorrect information, normalizing the data to ensure that all variables have similar ranges, and splitting the data into training and testing sets.
3. Model Selection: The next step is to select an appropriate machine learning algorithm for the task of CubeSat health monitoring. There are a wide range of algorithms to choose from, including decision trees, random forests, neural networks, and support vector machines. The choice of algorithm will depend on the specific requirements of the problem, such as the type of data being used and the complexity of the problem.
4. Model Training: Once the appropriate algorithm has been selected, the model must be trained on the training data. This involves using the training data to fit the parameters of the model, so that it can be used to make predictions about the health of the CubeSat. The training process should be monitored to ensure that the model is not overfitting the data, which would result in poor performance on new data.
5. Model Validation: After the model has been trained, it must be validated to ensure that it is accurate and reliable. This involves using the testing data to evaluate the performance of the model, and comparing its predictions to the actual CubeSat health data. The model should be validated using metrics such as accuracy, precision, recall, and F1-score.
6. Model Deployment: If the model has been validated and found to be accurate, it can be deployed for use in real-world CubeSat health monitoring. This involves using the model to make predictions about the health of the CubeSat in real-time, and using these predictions to identify and respond to potential faults.

To achieve this goal, first, it is needed to find the suitable algorithm for problem. For this purpose, machine learning algorithms, which are mathematical models that utilize data to make predictions, offer several particularly efficacious solutions for CubeSat health monitoring [18]. These algorithms include:

- **Decision Trees**: Decision trees are a type of algorithm well-suited for CubeSat health monitoring, as they handle complex data relationships and make predictions based on multiple inputs. The algorithm works by recursively partitioning the feature space into a tree structure based on the best feature to split the data, determined by a criterion such as information gain or Gini impurity. The tree structure can be used to make predictions by following branches from the root node to a leaf node, where the prediction is based on the majority class of samples in the corresponding partition. The process continues until a stopping criterion, such as maximum tree depth or minimum sample count in a leaf node, is met [19]. The formula behind that can be like below:

$$Info\ Gain = E(Parent) - \sum(w * E(Child)) \quad (1)$$

Where w is the weight representing the proportion of the data instances in a particular child node.

$$Gini\ Index = 1 - \sum(p(i)^2) \quad (۲)$$

Also, Entropy measures the amount of uncertainty in a set of instances. It is calculated as:

$$E = -\sum\Big(p(i) * log2\big(p(i)\big)\Big) \quad (3)$$

Where $p(i)$ is the probability of an instance belonging to a particular class i.

These mathematical concepts form the basis of the Decision Tree algorithm, which uses a tree-like structure to make predictions based on the attributes of the data instances. The algorithm recursively splits the data based on the attribute that results in the highest Information Gain or the lowest Gini Index, until the termination criteria are met. The final result is a tree structure that represents a series of decisions that lead to the prediction of the target variable [19].

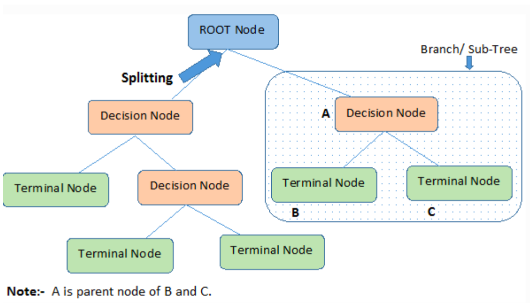

Fig. 2. Decision Tree Algorithm [19]

- **Random Forest**: The basic idea behind Random Forest is to generate an ensemble of decision trees, each of which is trained on a random subset of the training data. The final prediction is obtained by averaging the predictions of all the trees in the ensemble. The randomness in the subset selection and the use of decision trees help to reduce overfitting, which is a common issue in single decision tree models [20].
Each decision tree in the Random Forest consists of a series of nodes that represent conditions or decisions, and branches that connect the nodes. At each node, a feature is selected and the feature values are split into several intervals to create branches that correspond to different conditions. The final prediction is obtained by following the branches from the root node to a leaf node [20].

Neural Networks: Neural networks are a type of machine learning algorithm that are based on the structure of the human brain. They are particularly well-suited for CubeSat health monitoring, as they can handle complex and non-linear relationships between the inputs and outputs. Neural networks work by training multiple interconnected nodes, called neurons, to make predictions based on the data [21].

ANNs are inspired by the structure and function of the human brain. They can be used for a variety of tasks, including classification and regression analysis, in CubeSat health monitoring systems [21].

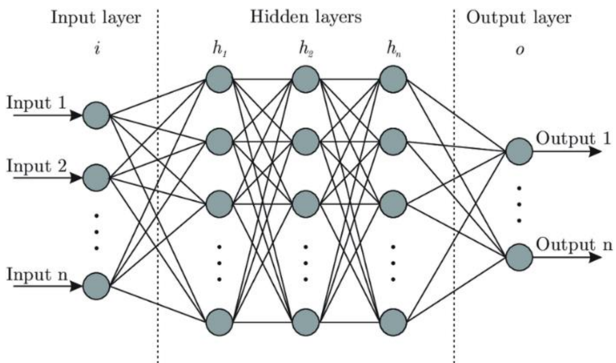

Fig. 3. Neural Networks [21]

The mathematical formula behind ANNs can be described as follows:

An ANN consists of a series of interconnected nodes, or artificial neurons, that are organized into layers. The input layer receives the feature vector x, which represents the telemetry data of the CubeSat, such as temperature, voltage, current, motion, etc. Each node in the input layer is connected to nodes in the next layer, which is known as the hidden layer. The hidden layer performs a nonlinear transformation on the input data, and passes the transformed data to the output layer. The output layer provides the final prediction for the CubeSat health status, based on the transformed data from the hidden layer.

Each node in the hidden layer performs the following computation:

$$z = \sum_{j}^{m} w_j x_j + b \quad (4)$$

where z is the output of the node, w_j is the weight for the jth feature of the feature vector x, x_j is the jth feature of the feature vector x, and b is the bias term. The activation function $f(z)$ is applied to the output z to introduce nonlinearity into the computation. A common activation function is the sigmoid function:

$$f(z) = \frac{1}{(1 + e^{-z})} \tag{5}$$

The weights and biases are learned from the training data by minimizing the prediction error using an optimization algorithm such as gradient descent. The optimization algorithm adjusts the weights and biases to minimize the difference between the predicted health status and the actual health status in the training data. By training an ANN on the training data, it is possible to make predictions about the health status of a CubeSat based on its telemetry data [21].

- **Support Vector Machines**: Support vector machines (SVMs) are a type of algorithm that are designed to handle linear and non-linear classification problems. They work by finding the boundary that best separates the data into two classes, and then using this boundary to make predictions. SVMs are particularly useful for CubeSat health monitoring, as they can handle high-dimensional data and make predictions based on multiple inputs [20].
  One-Class Support Vector Machine (OCSVM) is a type of Support Vector Machine (SVM) algorithm that is mostly use in unsupervised health monitoring system or anomaly detection problems.
  The mathematical formula behind OCSVM can be expressed as follows [20]:
  Given a set of n training samples in a d-dimensional feature space, the goal of OCSVM is to find the maximum margin hyperplane that separates the positive class (inliers) from the negative class (outliers) in the feature space. The OCSVM algorithm aims to find the hyperplane that maximizes the margin between the inliers and the closest outlier, while also keeping the outlier far away from the hyperplane.
  Mathematically, OCSVM solves the following optimization problem:

$$minimize \left(\frac{1}{2}\right) * \left||w|\right|^2 + \nu * \sum_{i=1}^{n}(\xi) \tag{6}$$

$subject\ to$:

$$y(i)(w^T x(i) + b) \geq 1 - \xi(i) and\ \xi(i) \geq 0 \tag{7}$$

  where w is the weight vector, b is the bias, $\xi(i)$ is the slack variable for each training sample, ν is the regularization parameter that controls the trade-off between the margin and the number of outliers, $x(i)$ is the i-th training sample, and $y(i)$ is the label for the i-th training sample (+1 for inliers, -1 for outliers).
  The optimal hyperplane can then be used for classification of new samples as inliers or outliers based on the sign of the decision function like this:

$$w^T x + b \tag{8}$$

- **K-Nearest Neighbors**: K-nearest neighbors (KNN) is a type of algorithm that is well-suited for CubeSat health monitoring, as it can handle complex data relationships and make predictions based on multiple inputs. The algorithm works by finding the k nearest data points to a given input, and using these data points to make a prediction [20].
  The mathematical formula behind KNN can be described as follows:
  Given a set of n samples, $x_1, x_2, \dots, x_n$, each with m features, where x_i is a m-dimensional feature vector and y_i is the corresponding target variable. The goal of KNN is to predict the target variable of a new sample x based on its k nearest neighbors in the feature space.
  The prediction y_{hat} of the target variable for a new sample x is given by:

$$y_{hat} = \frac{1}{k} * \sum_i sum\ (y_i)\ in\ nearest_{neighbors(x)} \tag{10}$$

  where $nearest_{neighbors(x)}$ is the set of k nearest neighbors of x in the feature space.
  In order to determine the nearest neighbors, a distance metric such as Euclidean distance or Manhattan distance is used to calculate the distance between the new sample and all the training samples. The k nearest neighbors are then selected based on the k smallest distances. In the context of CubeSat health monitoring, the feature vectors x can represent various telemetry data such as temperature, voltage, current, etc., and the labels y can represent the health status of the CubeSat. By training a KNN model on the training data, it is possible to make predictions about the health status of a CubeSat based on its telemetry data [20].

These algorithms can be used alone or in combination to build machine learning models for CubeSat health monitoring. The choice of algorithm will depend on the specific requirements of the problem, such as the type of data being used, the complexity of the problem, and the desired accuracy of the predictions. By using these algorithms, researchers and engineers can develop accurate and reliable machine learning models for CubeSat health monitoring, ensuring the long-term success of CubeSat missions [7].

The Machine Learning approach for CubeSat health monitoring is an innovative and promising solution that leverages the power of advanced mathematical algorithms to make predictions based on data. This approach utilizes algorithms such as decision trees, random forests, neural networks, support vector machines, and k-nearest neighbors to analyze large amounts of data and identify patterns and relationships that can be used to predict the health status of a CubeSat. This approach offers significant advantages over traditional methods, such as increased accuracy, the ability to handle complex data relationships, and the ability to make predictions based on multiple inputs. The future of CubeSat health monitoring will likely be dominated by this approach, as it offers a flexible and reliable solution that can be adapted to the changing needs of CubeSat missions [7].

An example of a machine learning approach to CubeSat Attitude Determination and Control System (ADCS) monitoring using the Support Vector Machine (SVM) algorithm would involve the following steps [15, 22]:

1. Data collection: Collect a dataset of readings from sensors such as angular velocity, magnetic field, and position, as well as control inputs and outputs from the actuators.
2. Data preprocessing: Clean and preprocess the data to remove any noise or outliers, and to ensure that the data is in a suitable format for the SVM algorithm.
3. Model training: Train a SVM model on the preprocessed data. The SVM algorithm will learn patterns and relationships in the data, and use these to make predictions about the ADCS behavior.
4. Model evaluation: Evaluate the performance of the SVM model by testing it on a separate dataset that has not been used for training. The evaluation will determine the accuracy of the predictions made by the model.
5. Model deployment: Deploy the trained SVM model to the CubeSat, where it can be used to make predictions about the ADCS behavior in real-time.
6. Monitoring: Use the predictions made by the SVM model to monitor the CubeSat's ADCS and detect any anomalies that may indicate faults. Any differences between the predictions and the actual readings from the sensors can be used to trigger alerts, which can then be investigated and addressed.

In this way, the SVM algorithm can provide a data-driven approach to CubeSat ADCS monitoring, which can detect faults in the system and enable effective maintenance and repair of the CubeSat (**Fig. *4***) [15].

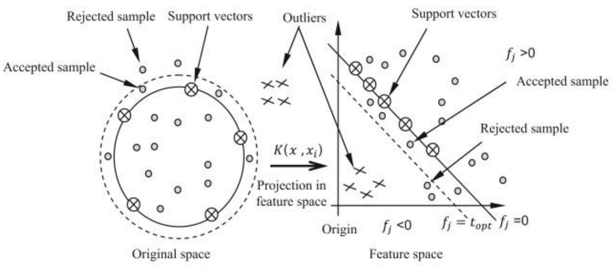

Fig. 4. OCSVM algorithm for detect anomaly [22]

Model-Based Approach

The Model-based approach to CubeSat health monitoring involves developing a mathematical model of the system and using this model to predict its behavior and detect any faults. This approach can be implemented in several steps [14]:

1. System Modeling: This involves developing a mathematical representation of the CubeSat system, which can include physical models of the components, as well as models of their interactions and relationships.
2. Data Collection: Data on the CubeSat's behavior is collected and used to refine and validate the system model. This data can be collected through onboard sensors or through telemetry.
3. Model Validation: The collected data is used to validate the system model and ensure that it accurately represents the CubeSat's behavior. Any discrepancies between the model and the data are used to improve the model.
4. Fault Detection and Diagnosis: Once the model has been validated, it can be used to detect faults in the CubeSat system. This is achieved by comparing the model's predictions with the actual behavior of the CubeSat and identifying any differences. These differences can then be used to diagnose the fault.
5. Predictive Maintenance: The model can also be used to predict potential failures in the system and prevent them from occurring. This is achieved by monitoring the system's behavior and predicting when maintenance or replacement of components is required.

Model-based approaches have been successfully applied to various areas of CubeSat health monitoring, including fault detection and diagnosis, predictive maintenance, and performance analysis. Researchers and companies in this field include the European Space Agency (ESA), the National Aeronautics and Space Administration (NASA), and private companies such as Thales Alenia Space.

An example of using a model-based approach for health monitoring of the Attitude Determination and Control System (ADCS) subsystem (**Fig. *5***) of CubeSats is through the use of the Unscented Kalman Filter (UKF) algorithm. The UKF algorithm is a state estimation algorithm that uses a mathematical model of the CubeSat's dynamics to estimate its internal states, such as the attitude and angular velocity [23].

For example, the mathematical model of the CubeSat's dynamics is used to estimate its internal states based on measurements from onboard sensors. The UKF algorithm uses this information to determine the most likely values of the internal states and the uncertainty associated with these estimates [23].

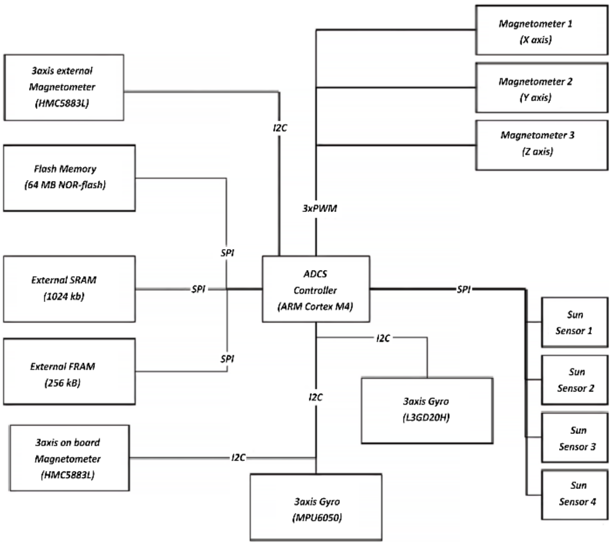

Fig. 5. ADCS System Block Diagram [24]

This information can then be used to perform health monitoring of the ADCS subsystem by detecting and diagnosing faults in the subsystem. For example, if the estimated values of the CubeSat's internal states deviate significantly from their expected values, it may indicate a fault in the subsystem. This example demonstrates how a model-based approach, specifically the UKF algorithm, can be applied to the health monitoring of the ADCS subsystem of CubeSats. The UKF algorithm is a well-established algorithm in the field of state estimation and has been widely used in many control systems and health monitoring applications [23].

Trends and Future Directions

In the field of CubeSat health monitoring, several trends have emerged that are shaping the future of this area of research and development. These trends include:

- Increased use of machine learning techniques: The development of advanced machine learning algorithms and techniques is leading to increased use of these tools in CubeSat health monitoring. Machine learning techniques allow for the analysis of large amounts of data in real-time, providing critical information for health monitoring and enabling quick response to potential problems [5].
- Integration of multiple approaches: As CubeSats become more complex, the integration of multiple health monitoring approaches, such as onboard sensors, telemetry, and fault detection and diagnosis, is becoming increasingly important. This integration allows for a more comprehensive understanding of the CubeSat system, providing a more complete picture of its health [2].
- Development of miniaturized onboard sensors: The development of miniaturized onboard sensors is allowing for the collection of more detailed data from CubeSats, providing critical information for health monitoring. This trend is driven by the need for CubeSats to be as small and lightweight as possible, while still providing the necessary data for health monitoring [8].
- Increased use of wireless communication: The increasing use of wireless communication, such as LEO satellite networks, is enabling the rapid transmission of data from CubeSats to ground stations, providing critical information for health monitoring and enabling quick response to potential problems [16].
- Advancements in data analysis and modeling: The development of advanced data analysis and modeling techniques is allowing for a more comprehensive understanding of CubeSat health and performance. This trend is driven by the need for more accurate and reliable health monitoring information, as CubeSats play an increasingly important role in space exploration and other applications [4].

In conclusion, the trends in CubeSat health monitoring are driven by the need for more comprehensive and reliable health monitoring information, as CubeSats become more complex and play an increasingly important role in space exploration and other applications. The integration of multiple approaches, the development of miniaturized onboard sensors, the increased use of wireless communication, and advancements in data analysis and modeling are shaping the future of this field.

Conclusion

In conclusion, CubeSat health monitoring systems have become increasingly important as the number of CubeSats in orbit continues to grow. These systems play a crucial role in ensuring the longevity and reliability of CubeSats and their subsystems. A number of different approaches have been developed for CubeSat health monitoring, including both model-based and machine learning-based approaches.

Model-based approaches use mathematical models to describe the behavior of CubeSats and their subsystems, and use this information to diagnose and predict issues. Machine learning-based approaches use data-driven techniques, such as deep neural networks and decision trees, to detect and diagnose issues in real-time.

While both approaches have their strengths and weaknesses, machine learning-based approaches have emerged as a promising solution for CubeSat health monitoring. These approaches have the ability to learn from data, making them well-suited to detect and diagnose complex issues in real-time.

In the future, it is expected that the development of CubeSat health monitoring systems will continue to be an active area of research. The focus will be on improving the accuracy, reliability, and cost-effectiveness of these systems, as well as on developing new techniques for monitoring CubeSats and their subsystems.

Overall, the review of the existing research on CubeSat health monitoring systems highlights the importance of this field, and the potential for future developments to improve the reliability and longevity of CubeSats.

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