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An Adaptable Fault Detection Method in Engineering Systems Using Machine Learning

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Abstract

In the realm of system engineering, efficient and rapid fault detection is crucial for maintaining operational safety and performance. Traditional fault detection methodologies often depend on extensive system-specific knowledge and are designed to identify only predefined faults, limiting their broader application. This paper introduces a novel machine learning-based fault detection approach that leverages minimal system inputs to model normal operating conditions. Unlike traditional methods, our approach does not require detailed expertise about specific fault conditions. In-stead, it detects deviations from normal behavior, flagging these as potential faults. This model assumes that any significant discrepancy between expected and actual sensor data indicates a fault, thereby simplifying the fault detection process and enhancing its applicability across various systems. To validate the effectiveness of this approach, we conducted experiments on a quad-copter, focusing on motor and external disturbances. The results demonstrate that our model can successfully identify faults without prior knowledge of specific fault types, offering a flexible and scalable solution for various industrial applications. The simplicity and adaptability of this method make it particularly attractive for systems where traditional fault detection techniques may be impractical due to complexity or the need for rapid deployment.

Keywords: Machine Learning, Fault Detection, Supervised Learning, Unmanned Aerial Vehicle (UAV)

1. Introduction

This paper proposes a data-driven, machine-learning-based approach for Fault Detection (FD), focusing on the relationships among measurable system parameters. A practical implementation is demonstrated through a case study on a quadcopter, where motor faults are identified using onboard accelerometer and gyroscope sensors.

Conventional FD methods often rely on specific measuring tools, domain knowledge, and system-specific configuration, which require experienced operators and can be time-consuming. In contrast, the proposed model aims to minimize dependency on system expertise. It builds on the notion that every system comprises interdependent components, where a fault in one can influence others.

To achieve this, we adopt machine learning (ML) techniques, as Ahmad et al. [1] showed their capability in modeling complex, nonlinear system behaviors.

2. Literature review

Fault Detection (FD) has traditionally relied on historical system data and explicit knowledge of known fault conditions. However, modern approaches increasingly favor machine learning (ML) to reduce this dependency. Several studies [2-6] have successfully implemented ML techniques to enable data-driven FD systems.

Feierl et al. [7] proposed a purely data-driven FD algorithm that does not require domain-specific knowledge. Similarly, López-Estrada et al. [8] used ML to construct implicit models for detecting actuator faults in UAVs, based on onboard sensor data.

Despite these advancements, a major limitation remains: most classification-based FD approaches depend on data from known fault conditions [7], which may not always be available.

Our proposed methodology addresses this gap through the following process:

- Model the system in its healthy state using ML techniques and available sensor data.
- Continuously compare the predicted behavior with real-time sensor readings.
- Generate fault alerts when significant deviations are detected.

The key innovations of this method are outlined as follows:

1) In numerous articles, the Random Forest (RF) method has been utilized. RF typically involves repetitive application of a fixed number of decision trees.[7] our

method introduces a new framework called Decision Set (DS), which is constantly evolving and expanding.

2) We have formulated a novel concept utilizing a unique method known as the DS. This approach enhances ML's focus on the range of the answer and improves accuracy by maintaining certain parameters constant.
3) ML algorithms generally require two types of data: data from when the system is healthy and data from when faults occur. Given the challenges and time requirements to identify all system faults or simulate real fault conditions, our approach focuses exclusively on data from the healthy state for FD.
4) Conventional FD methodologies frequently fail to generalize beyond the range of values encountered during training sessions. As a result, they are incapable of predicting values that fall outside predefined thresholds, leading to a significant incidence of false alarms. The method proposed in this study addresses this limitation through innovative modifications designed to enhance the algorithm's generalization capabilities across diverse operational scenarios. In this regard, we employed the Creative Neighborhood DS method.
5) In the standard RF method, a single data instance is utilized across various decision trees, with each tree's responses evaluated independently. Contrarily, our method employs varying DS for FD, adjusted according to operator commands. This adaptability allows for the initiation of a new DS and termination of the previous one as determined by the operator.
6) Unlike other studies, our research does not eliminate all correlated parameters indiscriminately. We first categorize measurable parameters and then selectively remove one of two highly correlated parameters within the same category.
7) Whereas existing research in FD often concentrates on a single system parameter such as vibration signals or acoustic waves, our research emphasizes the interrelationships and impacts of multiple measurable parameters.
8) Employing ML in FD allows for the effective analysis of large data volumes, extraction of patterns, and precise predictions, thus enhancing the capability to identify faults across various domains.

3. problem definition

In many engineering systems, fault detection is challenged by limited access to labeled fault data, dependency on expert knowledge, and the need for system-specific configurations. This study addresses these limitations by proposing a machine learning-based approach that detects faults using only the relationships among a small set of measurable parameters in the system's healthy state. Rather than relying on predefined fault patterns, the method identifies abnormalities through deviations from the expected behavior learned from normal operations.

To validate this approach, a quadcopter system is used as a case study. The proposed method aims to detect the timing of fault occurrences—such as motor malfunctions or structural imbalances—without requiring complete knowledge of the system's internal dynamics or explicit fault models. This enables broader applicability and reduces reliance on costly instrumentation or expert-tuned thresholds, making the model both practical and scalable for real-world scenarios.

4. Model execution steps

The proposed FD model operates in four stages:

Step 1: Parameter Selection

Identify and classify measurable parameters using existing or installable sensors. Parameters are grouped into two main categories.

Step 2: Model Construction

Apply nonlinear regression functions (using Python's scikit-learn) to the DSs. In our study, each DS corresponds to a unique angle and magnitude of acceleration.

Step 3: Real-Time Estimation and Alerting

At each time step, the system estimates target parameters and compares them with actual sensor values. A fault alert is triggered if deviations exceed the acceptable threshold.

Step 4: Adaptive Retraining

The initial DSs may not represent all system behaviors. Therefore, the model includes a continuous retraining mechanism to ensure adaptability under evolving operational conditions.

5. Case study

The case study focuses on detecting motor faults in a quadcopter. To simulate a controlled fault, an iron washer was attached to one of the quadcopter’s arms (Arm No. 3), creating an imbalance that mimics a motor failure.

- **Figure 1** shows the deviations between predicted and actual acceleration values under fault conditions.
- **Figure 2** illustrates how the predicted and actual values diverge along all three axes when a failure occurs.

This experimental fault was successfully detected without needing domain-specific configurations, highlighting the generalizability and practicality of the proposed model for FD in real-world applications.

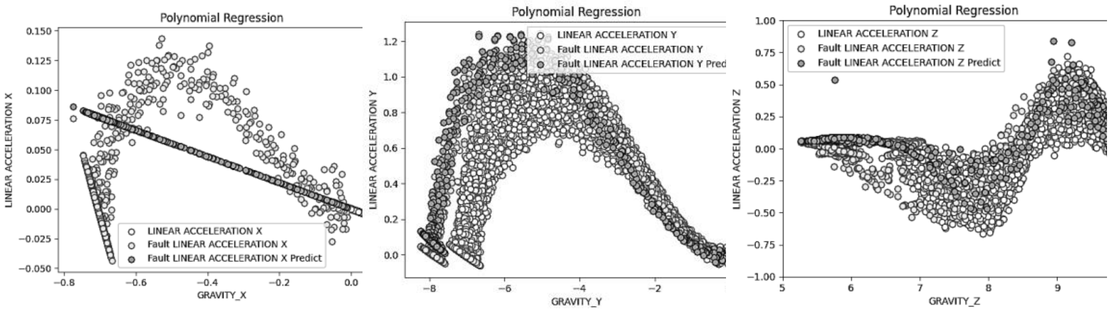

Figure 1. Comparison of acceleration parameters in system health and fault status

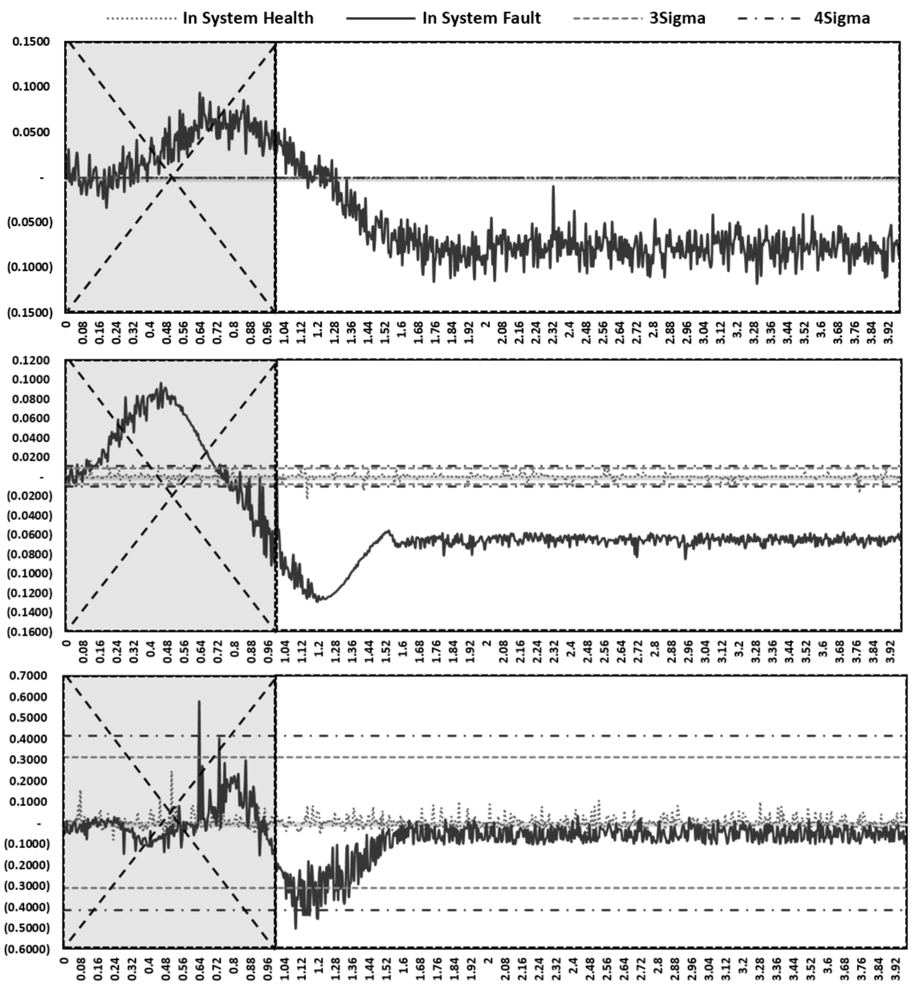

Figure 2. The value of the estimated acceleration and the actual acceleration of the system in the direction of the (a) X vector , (b) Y vector, (c) Z vector

6. Conclusion

In this study, we propose a machine learning-based fault detection (FD) method that operates without requiring expert knowledge or specialized tools. The approach models the system's expected behavior using a small set of measurable parameters obtained from its healthy state. Faults are detected by identifying deviations between predicted and actual sensor readings. The method was validated on a quadcopter and successfully detected motor faults as well as external disturbances. It is adaptable to various systems and easy to implement. Future work will focus on localizing fault sources and incorporating additional sensor data to further enhance accuracy and reliability.

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