Machine Learning Techniques for Automatic Sensor Fault Detection in HUMS Systems

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Abstract
In this paper we describe the problem of developing sensor fault detection within HUMS instrumentation systems, and solutions based upon machine-learning techniques. We conclude with a report on our proof-of-concept demonstrator, and outline next-steps towards implementation of a autonomous selfdiagnostic sensor solution.

1. INTRODUCTION

Good data is key to the success of a health and usage monitoring (HUMS) program, and modem data acquisition systems allow for reliable, high fidelity data capture. Unfortunately HUMS programs are often hindered by undetected sensor and wiring problems that can lead to invalid data and inconclusive analysis.
Many authors have identified sensors and wiring as the weakest link in an entire HUMS system (e.g. [1], [2]), where the transducer and consistency of the transducer/structure interface can "make or break" a system. Choosing long-life sensors with lifetimes in excess of assets under test is one approach for addressing this problem, however these high cost and high specification sensors are rarely economically viable. Traditionally for airborne health monitoring programs, there is a realistic expectation that sensors will be replaced over time, and that dedicated data analysts will be available to spot subtle signs within data which indicate the onset of sensor/wiring faults. This approach does not scale well for large fleet deployments and does not allow for robust automation.
In this paper, we present new sensor diagnostic approaches based on "Machine Learning" techniques[1]. These automated techniques allow for reliable measurement using practical cost sensors, installed in extended duration monitoring programs spanning many years. Machine Learning fault detection techniques not only detect the obvious catastrophic sensor errors which clearly manifest themselves in captured data, but also the more subtle sensor issues that can easily go undetected for long periods of time, leading to less reliable structural analysis, e.g.

- strain gauge de-lamination
- accelerometer de-calibration
- dry solder joints (Fig. 1 left)
- loose wiring (Fig. 1 right)

A key enabler for airborne HUMS systems is the automation of human data analysis, allowing systems to operate reliably without intervention for many years. This paper explores how "Machine Learning" techniques can be used to detect subtle signs of sensor/wiring faults within captured data, essentially automating the experience of human analysts who must ensure captured data is good. Machine Learning techniques offer the ability to not just automatically track condition indicators, but to also learn what the optimal condition indicators are for a particular set of data driven features.

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In today's airborne data acquisition systems, built-in diagnostics are typically limited in scope to a single subsystem and in functionality to a small number of failure scenarios. The Machine Learning techniques explored in this paper offer new expanded diagnostic capabilities which go beyond individual electronics units to

provide system-wide diagnostics, encompassing all critical parts of a HUMS system.
The structure of the paper is as follows:

- Section 1 - Introduction
- Section 2 - Problem Statement
- Section 3 - Machine Learning Approaches
- Section 4 - Results
- Section 5 - Conclusion and Future Work

2. PROBLEM STATEMENT

The aircraft instrumentation units used to collect data for HUMS systems, must endure high environmental stresses during flight, most are designed to be rugged and are qualified under military grade standards (e.g. MIL-STD-810, DO-160). Units will often remain in the field for many years gathering data. Each instrumentation system captures most of its data from remotely located sensors, connected to the acquisition units via wiring of variable quality. Overall system performance for an aerospace instrumentation is affected dramatically when remotely connected sensors and/or wiring fail during operation.

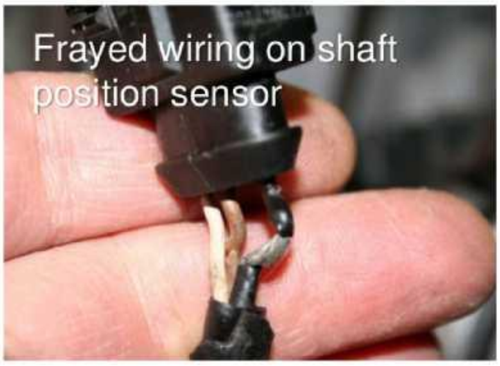

Figure 1 : Example sensor with catastrophic failures

When sensor and wiring problems go undetected for long periods of time, the results can be devastating as theHUMS system is supplied with junk data. It has been recognised in the literature for some time that sensors and wiring are the weakest link of an HUMS system [1,2], where the transducer can "make or break" the system.
In practise, instrumentation engineers must accept that sometimes sensors just go bad, and to ensure consistent good data they must track "condition indicators" within captured sensor data. When a fault is detected, the culprit sensor/wiring connection must be replaced before they affect test data. Consistent sensor and wiring fault tracking is very time consuming and difficult to achieve for monitoring systems that are left unattended for long periods of time.
An example strain gauge signal is shown in Fig. 2, the spikes indicate the onset of a wiring fault. To spot these events within a dataset takes considerable time, effort and experience. Traditionally dedicated data analysts use their learned experience to spot subtle signs indicating the onset of sensor/wiring faults. A key enabler for HUMS systems is the automation of human data analysis, allowing systems to operate reliably without intervention. In this paper we present initial results of our exploration of "Machine Learning" techniques, as way of detecting subtle signs of sensor/wiring faults within captured data, automating the experience of human analysts. Our ultimate aim is to provide instrumentation engineers and HUMS program managers with sensor level self-diagnostic capability.

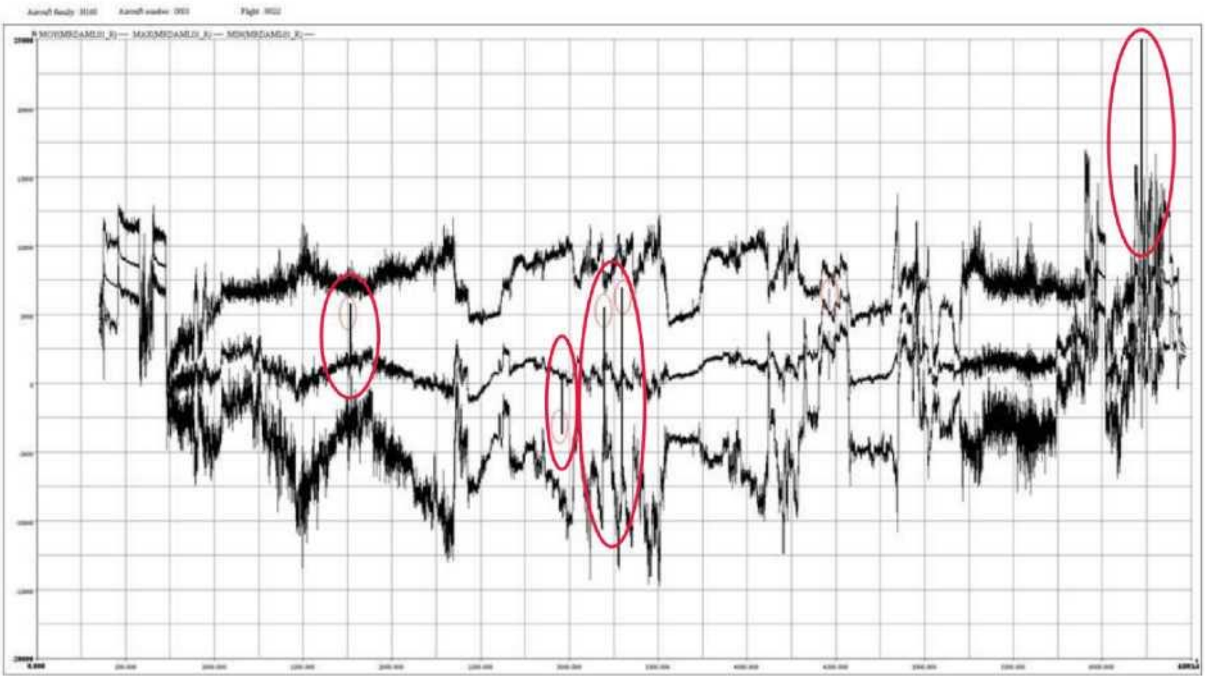

Figure 2 : Onset of wiring fault, manifesting itself as spurious spikes in time-series data.

3. MACHINE LEARNING APPROACHES

As an initial test case we have concentrated on very common sensor, a strain-gauge sensor embedded within a balanced Wheatstone bridge (see Fig. 3). This sensor is used to detect subtle displacements within mechanical structures and is a key component of most aerospace instrumentation systems. The faults seen for this sensor, and sensors generally can be both dramatic and subtle, wiring faults tend to be dramatic and catastrophic, biasing and de-balancing errors tend to be more subtle and harder to detect. The most useful self-diagnostic techniques are those that detect the subtle errors, those that represent the early onset of a problem.

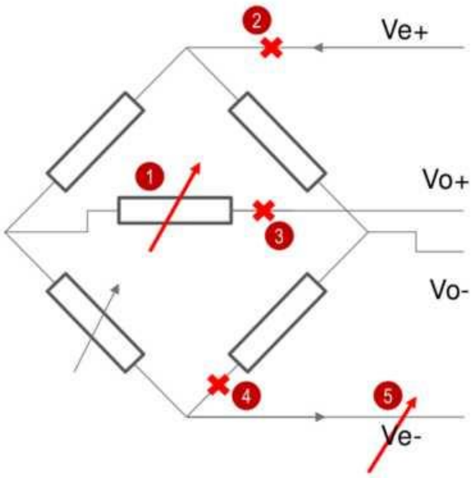

Figure 3 : Wheatstone Bridge sensor labelled with the five fault types ***{FI, F2, F3, F4,*** F5}

In our fault classification model we consider five of the most common fault types:
Fl: Bridge de-balance
F2: Excitation wiring break
F3: Output wiring break
F4: Bridge wiring break

F5: Excitation voltage degradation

In choosing a classification approach we consider several criteria as essential for successful approach.

Cl: The approach must be easily scalable from a small number of sensors, to hundreds and possibly thousands.
C2: It must be robust to multiple variations including different sensor types, different configurations, different aircraft and different environments.
C3: It must be intuitive and accessible by instrumentation engineers without a “Data Science” or “Machine Learning” background.

The strain-gauge sensor typically produces a continuous low-bandwidth signal during normal operation. An instrumentation system collects data samples over time to form “time-series” data. The machine learning task in the paper, is to examine the strain-gauge time-series data and classify the sequences according to the fault type present (or not present).

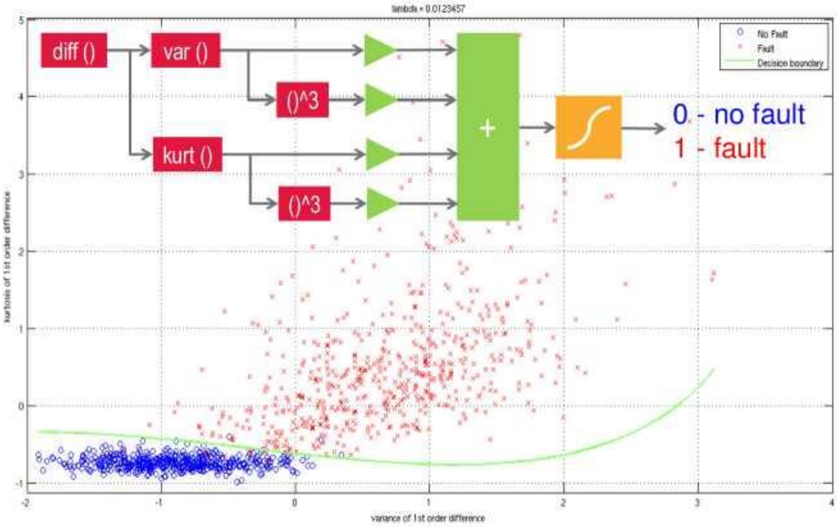

Figure 4 : Example Feature-based classification approach: Logistical

Regression classifier Several classification approaches are used for time-series

signals of this kind:

- **Feature-based Classification:** Feature-based methods transform the time-series data into feature vectors and then perform classification based on pre-learned feature space. Logistical regression is a classic example of a feature-based classification approach [4], where data features are passed through a set of pre-learned coefficients and combined to give an indication of classification type. These approaches have the advantage of greatly reducing dimensionality of data, but can involve specific tuning to applications by domain experts. An example logistical regression classifier is shown in Fig. 4, with a cubic decision boundary.
- **Model-based Classification:** Model-based methods construct models of the data for each class and classify new data according to the model that best fits it. Models can be statistical in nature where probability distributions such as Gaussian, Poisson, Markov, and Hidden Markov Models are used to represent data [5].

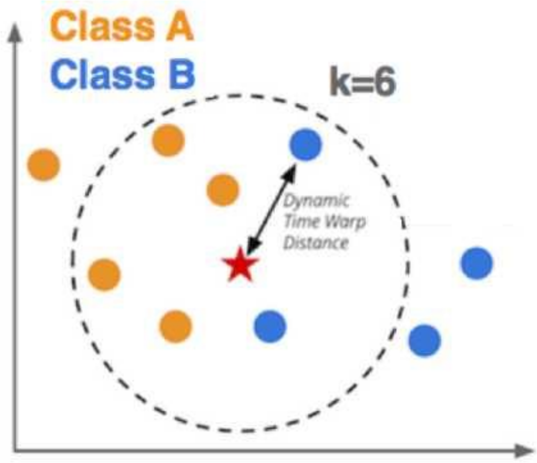

Figure 5 : Example Distance-based classification approach: k-Nearest Neighbours (k=6)

- **Distance-based Classification:** Distance-based methods such as k-Nearest Neighbour, compute (non-euclidean) distance between pairs of time-series. The method used to measure the distance (similarity) is crucial to the performance of the classification algorithm [3].

Feature-based classification offers elegant solutions with a reduced feature space that can be easily scaled to hundreds of sensor channels. Fig. 4 shows an example of such a classifier where features are combined with specific weightings. This small number of coefficients makes this approach scalable to many sensors (as per Cl), but there is specific training required for each new sensor, and configuration change etc., and a level of domain expertise is required during learning of new coefficients. Feature- based classification is not as accessible and intuitive as required by ***C3*.**
Model-based classification offers powerful solutions, but are even less accessible to non-experts ***(C3*** again).
Distance-based classification approaches are much more intuitive, classification is performed by directly comparing new data-points with data-points from training sequence, the new data-point takes on the classification of the closest points (see Fig. 5). This approach best meets C3. Distance-based classification is also agnostic to sensor types, and can adapt to configuration changes easily (as per C2). Although the same reductions in feature space are not available for this approach, large-scale installations (as per ***Cl***) are still possible by constraining the number of comparison points used. We conclude that a “distance-based classification” approach offers the best methodology for meeting our three criteria.

4. RESULTS

Our analytic approach involves three main steps:

1. System Modelling: Developing and maintaining an accurate model of the strain-gauge sensor. This model gives access to thousands of data-vectors of various permutations, allowing robust algorithm development.
2. Classification algorithm development, using a variety of distance-based classification approaches and data-vectors supplied by model.
3. Test and verification against real-world data. This stage will usually point to improvements to both model and algorithmic approach which can be fed-back iteratively, progressively improving the classification methods.

In this paper we report on results on a first pass through these three steps. A representative system model was created using real-world datasets and laboratory generated fault signatures. This model was then used to generate thousands of randomized data-vectors, an example is shown in Fig. 6.

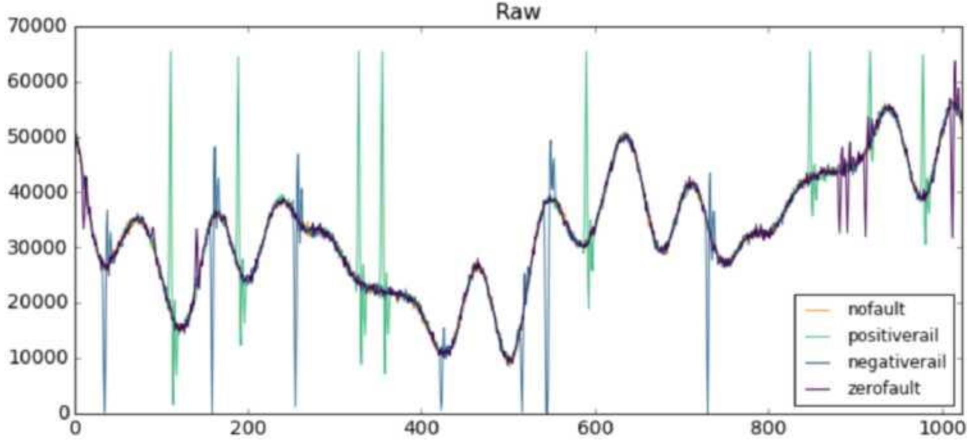

Figure 6 : example strain-gauge signal with fault types {***F2, F3, F4}***

The first candidate algorithm chosen was the kNN with a non-Euclidian distance metric, we chose $\boldsymbol{k} = 1$, such that classification is simply through comparison with 1 nearest neighbour. The literature reports that this approach "has proven exceptionally difficult to beat" (a conclusion reached by Xi et. al. [6] after conducting an extensive literature search of time-series classification problems). KNN itself is a long established method of classification which is simple and intuitive to implement. It works by comparing an unlabelled (unseen) data point to k neighbouring labelled (seen) data points from a training set. The unlabelled data point is then classified using the majority label among its k-nearest neighbours [7].To evaluate the results of the 1NN classifier we have applied a Train:Test split ratio of 23 : 13 to 400 randomly sampled but balanced data points where 200 are sampled from our normal signal dataset and 200 from the selected error set. This results in a training set of 268 samples and a testing set consisting of 132 after ratio rounding. We measure the performance using confusion matrices, precision, recall, and f1-scores.

Our initial results for the 1NN approach have been very encouraging as shown by the confusion matrices shown in Fig. 7. For railing type faults {F2, F4} we observed 100% success with scoring metrics all achieving 1.0. For the more subtle output wiring breaks {F3} we observed a 0.96 score.

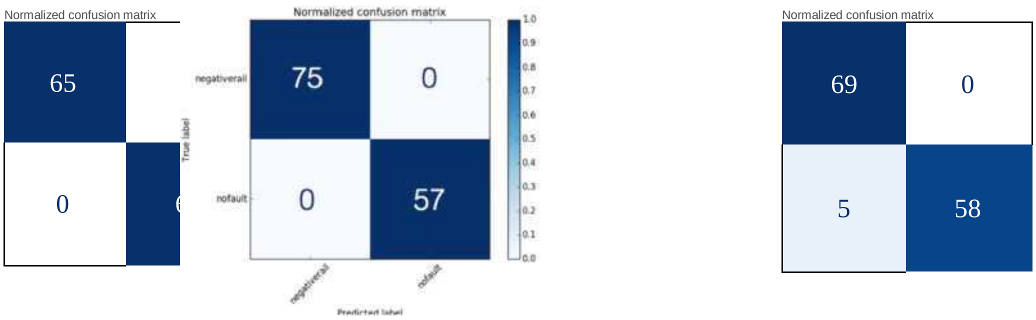

Figure 7 : Confusion matrix results for 1NN classification

5. CONCLUSIONS AND FUTURE WORK

In this paper we have reported on our proof-of-concept demonstrator, showing that machine-learning techniques can be used to detect and diagnose sensor faults in an automated fashion. Specifically we have demonstrated the ability of kNN to classify binary time series signals from a strain gauge as either normal or different error types within a high degree of accuracy. This approach is robust to the three success criteria ***{Cl, C2, C3},*** and will be prime candidate for evaluation as we move towards bench prototypes and field trials.

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