Evaluating Sensor Data Quality for Fault Detection and Diagnosis

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Fault Detection and Diagnosis

Fault Detection and Diagnosis (FDD) is the automated process of identifying errors within physical systems. A **fault** is a deviation from standard operating conditions and a **failure** occurs when a system can no longer preform a function. FDD systems attempt to detect **faults** before failures occur thus making systems more reliable and safer while reducing downtime and maintenance costs. The goal is to create FDD systems which are accurate, reliable and low cost.

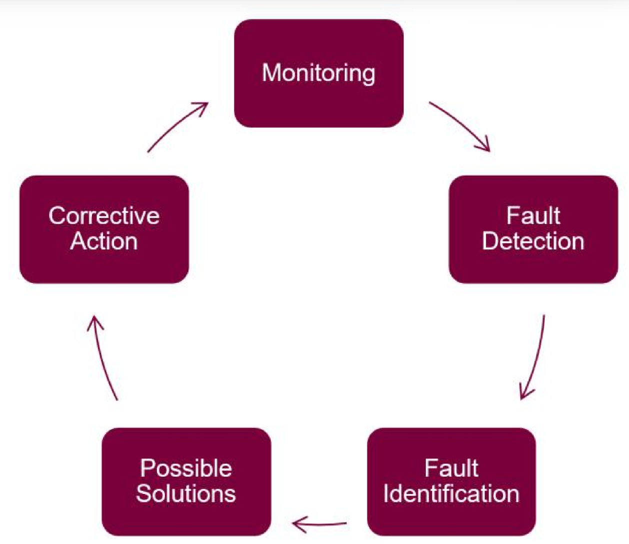

Figure 1. An ideal self-corrective cycle.

Figure 2. General steps of an FDD process.

Figure 3. Example of a FDD process for a system with a cracked ball bearing.

Problem

The majority of existing FDD research has been done with laboratory-grade setups and the effect that changing the test setup would have on performance is not clear. Relevant research questions:

- Can we **quantify** how much a particular sensor contributes to the performance of the FDD system?
- Can we **measure** if changes to sensor configurations result in significant changes to the processed data?
- Can we find the minimum required sensor setup for a specific FDD application?
- Can we find the best feature extraction method for a particular dataset to maximize it's classification usefulness?

Thus, how can the quality of the data for classification be measured so we can know if changes in a process are resulting in improvements to the data.

Current Methodology

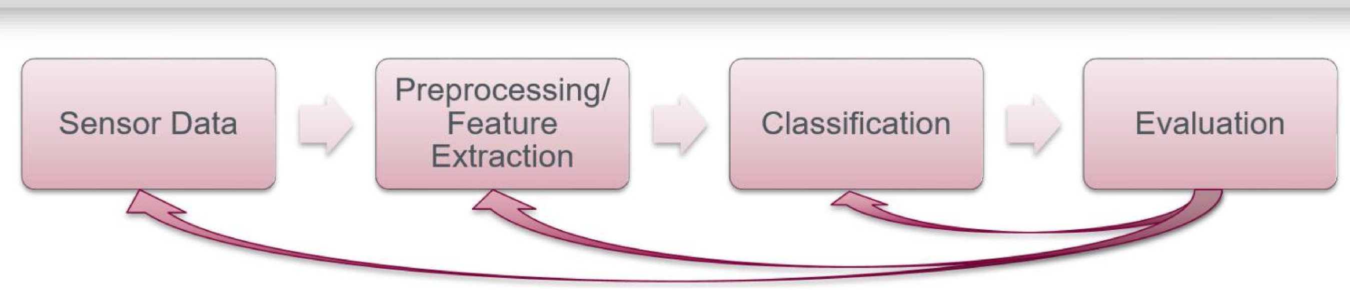

Figure 4. Evaluating the performance of an FDD setup based on final output.

Currently, final classification accuracy is used to evaluate changes at every step of the process. Results can be highly dependant on classifier used and tuning models can be very time consuming. Small differences in the performance of other components in the system may be easily masked by the classifier's learning ability or variations introduced by the classifier.

Proposed Methodology

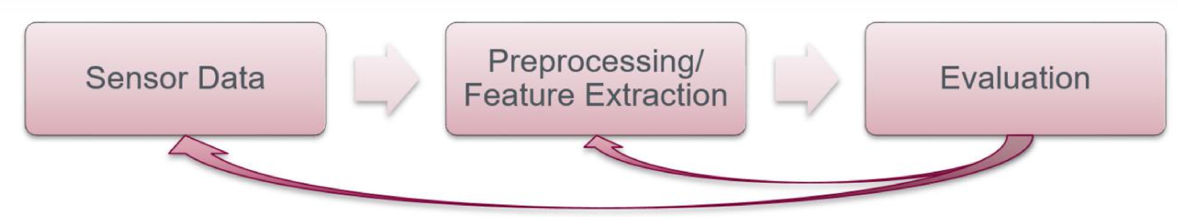

Figure 5. Proposed process for evaluating different sensors and processing methods.

Remove the classifier component and evaluate the performance of the sensors and processing based on the separability of the **dataset**. Benefits:

- Lower system complexity (increased explainability / easier to troubleshoot)
- Faster training / testing time
- Possibility for optimization or rapid testing of different methods

Applying a measure to the dataset at this stage could detect if relevant information is present in the data and improvements at this stage should result in improvements across all classifier types. There is also the potential for separability measures to be used for data process optimization such as optimal feature selection.

Data Complexity

Data complexity: a characteristic of the dataset that relates to the difficulty of the classification problem. [4]
Separability is a subtype of data complexity and the category most relevant to this application. It is an intrinsic characteristic of a **dataset** and describes how the data points from different classes mix together [3] or how clearly the decision boundary can be established. [2]

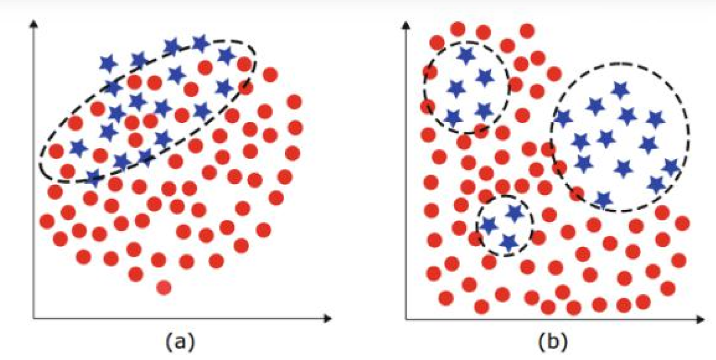

Figure 6. Two different cases of complexity in datasets. (a) Poor separability. (b) Small disjuncts. [2]

Types of separability:

- **Linear Separability**: a boolean property of a dataset. A two-class dataset is linearly separable if there exists at least one hyperplane (class boundary) that can separate the classes. [1]
- **General Separability**: a theoretical concept that allows for a spectrum of values.
  - **Geometric Separability**: based on the degree to which inputs associated with the same output cluster together. [5]
  - **Probabilistic Separability**: the separation of the class probability distributions.

Separability and Generalization

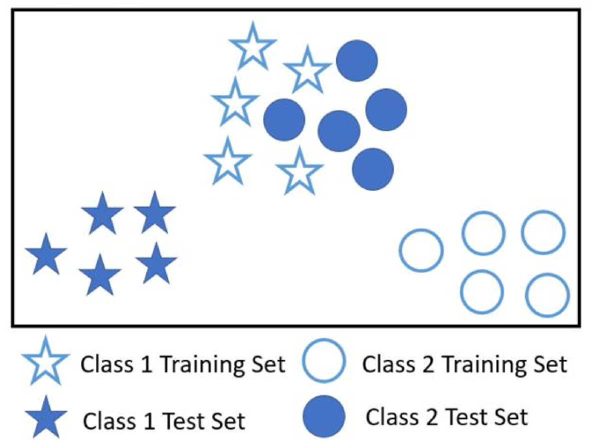

Figure 7. An example where both training and test data have high separability but low generalization.

Generalization: the ability to produce similar results on new data samples in comparison to performance on the training data.
Data needs to be separable and generalizable to insure accurate predictions in implementation. For example, it's possible to select features based on highest separability but lack generalizability such that the FDD process would act unpredictably on new data. Generalization can be estimated using separability measurements by comparing the same class across different sets or subsets.

Desirable Measurement Characteristics

The following are desirable characteristics in a measurement given the application to FDD and assumptions that can be made about the sensor data. Note: at the source, the noise can be assumed to be normally distributed but the distribution may change after processing.

- Measures general separability
- Is a global characteristic of a data set
- Allows comparison between different datasets
- Produces accurate and reliable results with a low number of samples
- Does not assume the probability distribution of classes
- Produces reproducible results
- Produces generalizable results
- Works on high-dimensional data (large number of features)
- Works on sparse datasets
- Has a low computation time
- Includes a confidence indicator for the result

Measurement: Probability Overlap

Estimating probabilistic separability by calculating the probability distribution overlap by approximating class probability distribution functions using Kernel Density Estimation.

Test: Measure the probably overlap relationship with the controlled variance on simulated datasets with different numbers of features.

Result: Failure as measure is impractical beyond datasets with more than 1 or 2 features. Exponential decrease in accuracy and increase in computation time as data dimensionality increases. Requires a large number of samples.

Future Work

Next steps: finding and confirming a measure can be used to differentiate processed data with good features from poor features using benchmark datasets on a simple FDD process. Fraction of Borderline Points, a measure which counts the points near the class boundary, shows promise for this application. It could be used to measure the separability and measure the impact of changing data processing parameters in an FDD process (for example, Figure 3) such as:

- Discrete Fourier Transform (DFT) window size and overlap
- Number of useful Principal Component Analysis (PCA) components

Ongoing research questions:

- How to best combine separability and generalization measures into a single value?
- How to best combine measures in multi-class cases?

References

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