State Reconstruction: Generating a Reference for Improved Diagnostics

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***Abstract*—Mechanical systems across most industries are mortal instruments, they will fail due to use or otherwise. Staying ahead of such catastrophes are crucial, especially in mission critical scenarios where loss of life is a very real danger. In such cases, corrective maintenance is too risky and scheduled maintenance is often costly; thus the collective shift towards predictive maintenance. Until recent advancements in artificial intelligence and sensor networks, such a strategy would not be so achievable. The 'predictive' aspect of thus type of maintenance implies that anomalies and failures are expected to be forecast ahead of occurrence - this can be accomplished with well placed sensors and sufficiently trained correlation methods. However, aspects such as shifting operating modes and varying sensor ranges make it difficult to make predictions solely using raw sensor data. This paper will outline methods and technologies to estimate healthy states of the monitored system to aid in the detection of failures before they affect function.Mechanical systems across most industries are mortal instruments, they will fail due to use or otherwise. Staying ahead of such catastrophes are crucial, especially in mission critical scenarios where loss of life is a very real danger. In such cases, corrective maintenance is too risky and scheduled maintenance is often costly; thus the collective shift towards predictive maintenance. Until recent advancements in artificial intelligence and sensor networks, such a strategy would not be so achievable. The 'predictive' aspect of thus type of maintenance implies that anomalies and failures are expected to be forecast ahead of occurrence - this can be accomplished with well placed sensors and sufficiently trained correlation methods. However, aspects such as shifting operating modes and varying sensor ranges make it difficult to make predictions solely using raw sensor data. This paper will outline methods and technologies to estimate healthy states of the monitored system to aid in the detection of failures before they affect function.M**

I. Introduction

Modern systems are increasing in complexity and sophistication, making it more and more difficult to identify the cause of a failure when it occurs. However, this is followed with advancements in sensor networks and the ability to process them. In the field of diagnosing a system for possible lack of function, analysis of specific variables - time-series' is key. This includes classification of particular failure, forecasting of future values and grouping of similar-behaving data points. To this end, AI and machine/deep learning has come to the limelight. Other works involving the state-space reconstruction such as Sam Yang's study on chaotic systems in modern machines [3] (a paper that has inspired this work) and usage of Singular Value Decomposition (SVD) in diagnostics [4] which focus on using domain-heavy strategies, involving a deep understanding of such systems to determine the reference/state space. While these methods work well with complicated, usually chaotic systems, much prior knowledge is required and solutions are constrained to a single problem. In addition to this, the focus is only in generating the reference signal but not to its extent in improving detection performance. To this end, this paper proposes methods to aid in the diagnostics by the use of a residual between the measured signal and a generated reference signal i.e. reconstructing the state space for any general system.

II. Materials and Methods

A. Hypothesis

The idea that having access to a reference state when distinguishing odd or anomalous behaviour is not uncommon, however, in most of these applications, a naive strategy of classification on the raw data is used. I.e. the reference is 'learnt' via training; in supervised methods, the reference is labelled (possibly as healthy) and in unsupervised, the structural information is used. The hypothesis that is explored is the advent use of the difference between a pre-generated reference and the raw time-series exceeds performance over the aforementioned strategy.

B. Data Set

The data set we used is Set No. 2 of the NASA bearing data set [1], which describes a specific test-to-failure experiment on a bearing test rig. One accelerometer was installed on each of the four bearings on a shaft. There are 984 files with 4 channels in the data set, each of which represents a 1-second vibration signal snapshot collected at a certain time point as the file name indicated, and consists of 20, 480 points.

C. Algorithms

All the algorithms implemented for the experiments can be found in the Python package `pyod` [2] and are listed below:

- K-Nearest Neighbours (KNN) Regressor
- Random Forest (RF) Regressor
- Gradient Boosting (GB) Regressor
- Local Outlier Factor (LOF)
- Isolation Forest (IF)
- One-Class Support Vector Machine (OCSVM)

III. Results

A. Experimental Setup

1) Data Preparation: To prepare the data, firstly we aggregated all the data points in each file by calculating the mean absolute values of the vibration recordings per channel and then merged them into one single data frame. Secondly, we split the data into training and test set. The training data was selected from 2004-02-12 11:22:39 to 2004-02-13 23:42:39 where the system was in a normal state, which means that we were doing a novelty detection task where the training data is not polluted by outliers and the goal was to detect whether a new observation is an outlier, rather than an outlier detection task where the training data contains outliers. The remaining part of the data set starting from 2004-02-13 23:42:39 was the test data leading up to the outer race failure that occurred in bearing 1. It is worth mentioning that even though there was only a failure that occurred only in bearing 1, the other bearings suffered from the vibration of the system and their senor values reflected this as shown in the validation data in Figure 1.

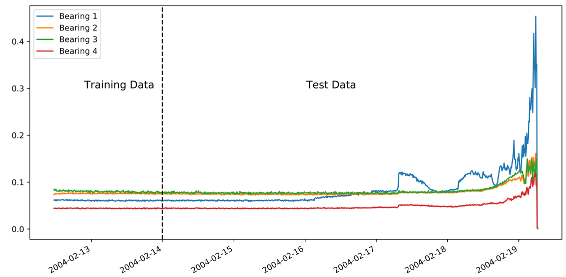

Fig. 1. Training and test data

2) Reference Generation: For reference generation, we first used a Min-Max Scaler to scale the training and test data, then we used a specific regressor for generating the references including training and prediction steps. The input and reference test data generated by Random Forest Regressor are illustrated in Figure 2 as an example. The reference test data indicate the healthy states of bearings, and it remains steady and roughly in a line, while the measurement test data were steady at the beginning and increased from gradually to rapidly when there was a failure occurring. After that, we calculated the differences between the scaled data and the corresponding reference data as the input for the next step. Please notice that this step is ignored in the experiments where there was no reference generator used, referred to as "No RefGen" experiments.

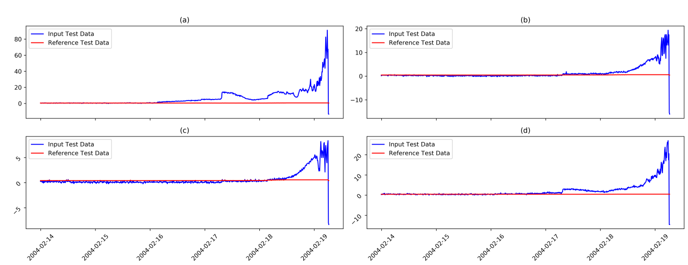

Fig. 2. Test data and reference: (a) Bearing 1; (b) Bearing 2; (c) Bearing 3; (d) Bearing 4

3) Data Reshaping and Labelling: Before diving into the anomaly detection step, we manipulated the above-mentioned training and test difference data by creating snapshots of it with 30% overlaps. We extracted 10 points per snapshot per sensor, which resulted in 30 training snapshots and 108 test snapshots. Then we reshaped the data as two dimensions where the first dimension indicates the number of snapshots, and the second dimension merged the sensor and point dimensions. In the meantime, we assigned labels for test data to evaluate the performance of anomaly detectors: the first 68 snapshots were labeled as normal and the rest were regarded as abnormal based on direct observations.

4) Anomaly Detection: In this step, we used a Min-Max Scaler followed by Principal Component Analysis with four components for pre-processing the input data, and then different anomaly detectors were experimented with for detecting failures in the system.

Figure 3 of two y-axes shows the original data and predicted labels in two experiments where either "No RefGen" or Random Forest Regressor was used with Isolation Forest as the anomaly detector. 1 represents normal data and -1 represents abnormal data. Both experiments were able to point out the abnormal data prior to the failure occurring, but a large amount of normal data was misclassified as abnormal in the "No RefGen" experiment, around 89.71% based on the confusion matrix in Figure 4, while the other demonstrates a better accuracy in classifying the data, which is 81.48% in contrast to 43.52% of the "No RefGen" experiment. The results can be improved further by fine-tuning the reference generation models.

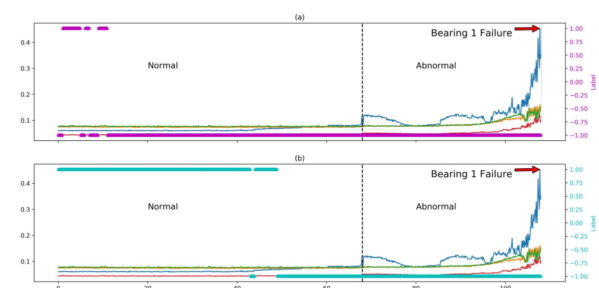

Fig. 3. Test data and predicted labels: (a) no reference generator was used: the magenta color indicates the anomaly labels; (b) random forest regressor was used: the cyan color indicates the anomaly labels

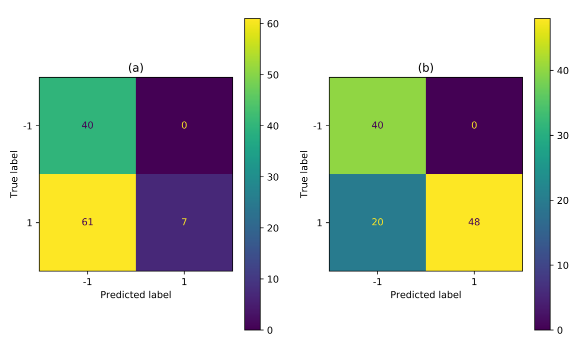

Fig. 4. Confusion matrices: (a) no reference generator was used; (b) random forest regressor was used

B. Results Table

All the experiment results are shown in Table I including the above-mentioned examples. The main variable in the experiments is the reference generator, either no reference generator or a specific reference generator was used: one of the K-Nearest Neighbours (KNN) Regressor, Random Forest (RF) Regressor, and Gradient Boosting (GB) Regressor. The other experiment variable is the anomaly detector and one of the Local Outlier Factor (LOF), Isolation Forest (IF), and One-Class Support Vector Machine (OCSVM) was used in each experiment for validating the interpretation of results. Therefore, there are 12 combinations/experiments in total, and we further divided them into 3 groups based on which anomaly detector was used.

Ref. Generator	A. Det.	F1 Score	ROC
No RefGen	OCSVM	11.11%	52.94%
KNN Regressor	OCSVM	81.74%	84.56%
RF Regressor	OCSVM	82.76%	85.29%
GB Regressor	OCSVM	79.65%	83.09%
No RefGen	IF	18.67%	55.15%
KNN Regressor	IF	78.57%	82.35%
RF Regressor	IF	82.76%	85.29%
GB Regressor	IF	79.65%	83.09%
No RefGen	LOF	71.70%	77.94%
KNN Regressor	LOF	89.43%	90.44%
RF Regressor	LOF	86.67%	88.24%
GB Regressor	LOF	87.60%	88.97%

TABLE I
EXPERIMENT RESULTS

IV. DISCUSSION

In the experiment group where OCSVM was used, the F1 Score of No RefGen is 11.11%, which is around 70% lower than the rest. Accuracy and ROC AUC Score show a smaller difference but the increasing trend remains from Exp.1 to the others. Another observation is that these evaluation results fluctuated across multiple reference generators, but they are relatively stable and around 80%. Changing OCSVM to IF will improve the "No RefGen" performance to some extent, but it is still far below that of the others in the same group. The use of LOF will increase the metric figures of all the in-group experiments compared to the other groups, however, the use of reference generators always outperformed the rest quite distinctly.

Overall, it is evident that the incorporation of a reference generator significantly improved all the evaluation results including the F1 Score, Accuracy, and ROC AUC Score regardless of which specific reference generator

and anomaly detector were in use, which confirms the effectiveness of the extra reference generation step.

V. Conclusions

The paper has presented the use of reference signals in improving the performance of failure detection in complex systems as a general solution. A bearing system was used to test the hypothesis of a use of reference signals/reconstructed state space.

In the future, further methods to generate references in more complicated systems will be explored, particularly when it comes to chaotic environments.

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