Distributed fault detection: Exploring the application of data-independent compression and outlier ensemble techniques

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1 Introduction and problem description

With the increasing complexity of systems and the need of precise control thereof, fast and accurate fault detection has become a critical system component. Fault detection is the task of detecting a system failure of any kind as soon as possible [1]. Often, sensors are used to make measurements on the system in order to determine its current state. We propose a general approach to detect faults utilizing such measurements without constricting it to fit a particular system. The hypothetical context is however taken to be high-dimensional, that is, we concentrate on systems measured with an extreme large number of sensors. Finally, we limit our research to explore a distributed architecture as these are considered more reliable than central approaches [2].

Faults are assumed to be represented by outlying values in the sensor data which can appear in different types. Aggarwal [3] categorizes outliers in point-, contextual- and collective outliers. As no particular application is considered, our analysis does not focus on one specific type of outliers. However, outliers can be generated by different sources. Zhang et al. [4] identify errors, events and attacks as distinct sources. The errors here relate to occurrences of outliers caused by sensor faults or system noise. Events are the phenomena that change the state of the system. Clearly, errors can be distinguished as system noise and sensor faults [1], where both type of outliers are hard to distinguish from system faults.

2 Related work

Many related approaches to distributed fault detection exist, of which a few are summarized in this proposal. Additional relevant approaches and techniques will be studied in more depth during the proposed research.

Serdio et al. [5] propose a residual-based fault detection scheme which does not require prior knowledge of the faults. The pipeline consists of an off-line and on-line process. The off-line part entails selecting and combining sensors into optimal subsets. Correlating sensors are clustered into subsets, where only subsets with a high confidence level of detection are included in the final decision. The on-line part incorporates the compression of the clustered sensor signals by means of Principal Component Analysis (PCA). To detect outlying measurements, a VARMA model is deployed. A measurement is flagged as outlier if the residual between the VARMA predicted value and actual measurement exceeds a threshold. This threshold changes over time with the trend of the measurements.

Yan et al. [6] introduce the use of local compression based on random projections in combination with a central detection algorithm. They deploy random projections at each sensor node in the compressed sensing manner, that is, the number of measurements is reduced by means of projecting it on orthogonal unit-length random bases. Compression is conducted to reduce the communication costs, as each sensor node transmits the compressed representation to a central detector. The compressed measurements are then recovered to reconstruct the original signal. The reconstructed signals are centrally analysed for the presence of outliers based on a simple mode-rule.

Boem et al. [7] present the results of a distributed fault detection scheme resulting in a two-layered communication architecture. The ground level consists of the sensors which observe the system at a certain sampling rate, though not necessarily synchronous. The sensors transmit their measurements to the first level consisting of a distributed fault detection mechanism. This layer denoises the measurements and handles collisions. Decisions are made on the second level, by mutual exchange of continuous hypotheses corresponding to each measurement between the distributed fault detectors. Due to potential misalignment and delays on the ground level, a re-synchronization step is deployed on the second. Faults are detected through communication between the distributed fault detectors which extract the residual from a filtered discrete-time model. Residuals exceeding a detection threshold, computed by each fault detector separately, are considered faults.

Our preliminary literature study has revealed a gap when it comes to communication efficiency. As discussed in [8] the communication costs of a fault detection architecture is an important aspect in many critical sensor-based applications. Yan et al. [6] leverage compressed sensing in order to reduce the number of measurements to be transmitted from the sensors to a central detector, but in applications with strong bandwidth limitations or high distances their approach might lack functional requirements. Therefore, we propose a method that provides further communication cost savings besides computational benefits.

3 Contributions

3.1 Proposal and research directions

We propose a distributed approach to fault detection, where we use random projections to compress the high-dimensional sensor data. Starting on the local sensor-level, the measurements at each timestep t will be transmitted to a nearby semi-local detector collecting data from a subset of sensors. Before the semi-local detector conducts its computations to identify faults, the test data of dimensionality $1 \times n$ (with n the number of signals in the subset)[1] is compressed. The compressed representation is then obtained by Gaussian random matrices Φ of dimensionality $d \times n$ conform formula (1) with d and n referring to the compression and original dimensionality respectively. Here, s_i denotes the ith subset of signals.

$$z_i = \frac{1}{\sqrt{d}}\, \Phi_i\, [s_{i,1} ... s_{i,k} ... s_{i,n}]^T \tag{1}$$

This compression technique is expected to significantly speed up computations, without losing significant detection performance as the distances between measurements remain equal up to some small error [9]. For each timestep, every semi-local detector computes an outlier-score using a detection function $f(\cdot)$. This score is only transmitted if it exceeds a predefined threshold. The semi-local and central detector therefore only communicate in case a suspicious set of measurements is conceived, hence communication costs between the semi-local and local detectors are kept low. The central detector collects outlier-scores from the semi-local detectors and provides a final decision on timestep t given function $g(\cdot)$. We aim to explore basic but also advanced ensemble learning techniques, such as stacking, to get to this function. Despite this central component, outlier scores have already been computed semi-locally. If, therefore, the central detector is not operating properly, we can fall back on randomly picking one of the semi-local detection outputs.

The use of random projections as compression technique, makes this proposal beneficial in large-scale high-dimensional contexts due to its data-independent component. More common compression techniques also used in fault detection, such as PCA, require more computational expensive data analyses to compress the data at hand. Additionally, the low communication costs make this approach interesting for applications with low bandwidths or large distances between sensor network and control components. Figure 1 provides a schematic overview of this approach.

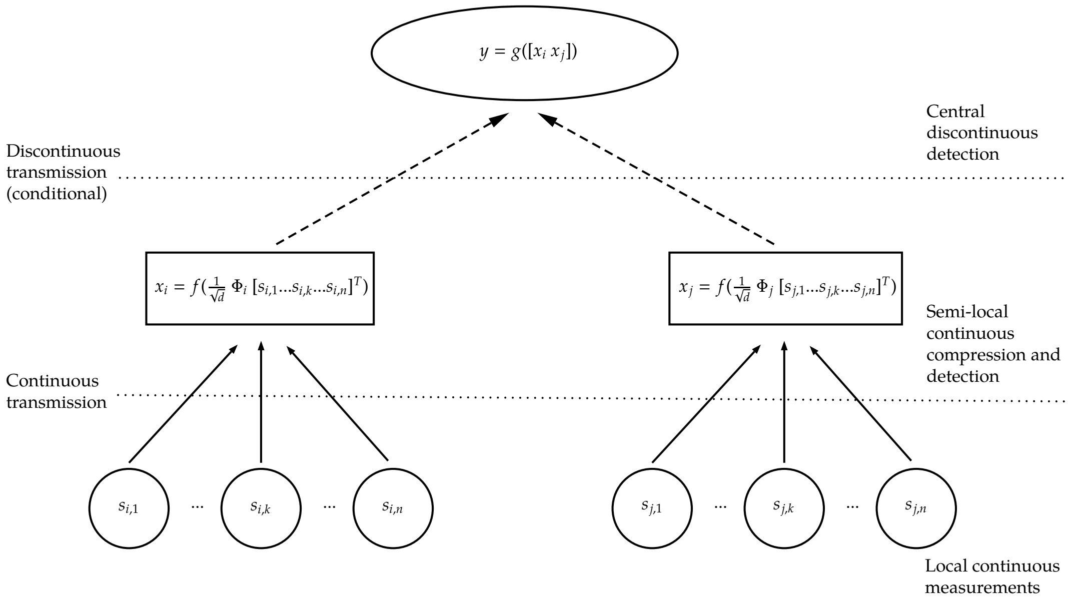


Figure 1: Schematic representation of the proposed approach

[1]Here, 1 corresponds to the measurements of a single timestep to be processed at a time. This batch can be larger if memory resources are sufficient.

Simply put, we will analyse the contexts in which the proposed approach is suitable. Therewith, we will identify the performance benefits and limitations. Our research will be guided by examining the following question:

> *How and to what extent can we boost fault detection performance leveraging Random Projections as weak-learners in a distributed detection scheme?*

More specifically we will make an attempt to answer at least the following questions:

- Does compression using random projections yield a proper representation for different feasible options of $f(\cdot)$ without losing performance compared to data-dependent compression techniques?
- To what extent can we compress the signal space, i.e. to what dimension can we compress what number of signals, without losing outlier significance in the data?
- Which methods can be used to cluster the sensors, taking the random compression base into account?
- What efficient ensemble learning techniques can we use to get to $g(\cdot)$?
- Can we enforce early detections by penalizing late detections more heavily?
- How can we make the proposed distributed approach applicable in streaming mode?

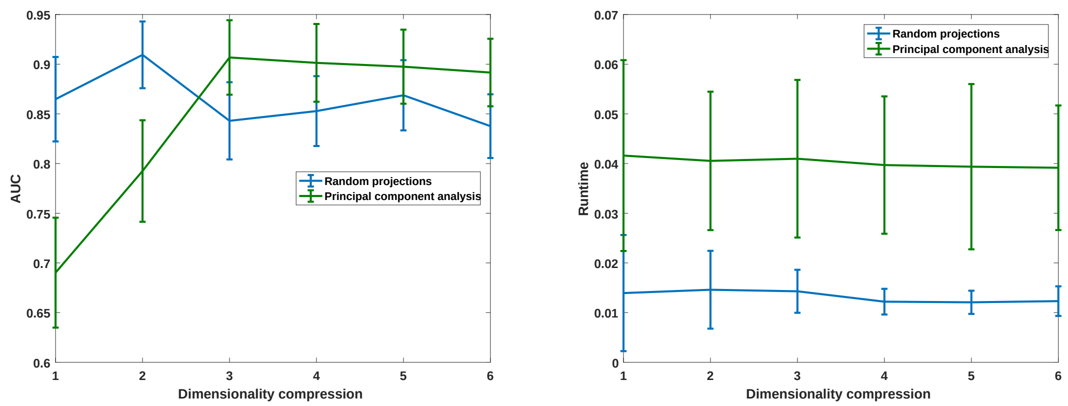
3.2 Preliminary results

We implemented a basic pipeline incorporating the distributed architecture as described in section 3.1. As we want to illustrate the potential of incorporating random projections in a distributed fault detection setup, functions $f(\cdot)$ and $g(\cdot)$ are kept simple for now. As outliers are considered to be representative for faults, the pipeline is now focused on the related task of outlier detection. The planned research will be focusing on fault detection in particular.

For these preliminary experiments, we used synthetically generated train and test data. For the train set we generated 150 signals from sine and cosine functions with random means between 0 and 2, and added noise terms $n \sim \mathcal{N}(0, 0.05)$. The test set consisting of 150 distinctly generated signals, are generated in the same way but are injected with respectively 13% and 18% point/contextual and sequential outliers in random subsets of the signals. This way, the test data is considered to be compliant with real-world situations where not all signals are responsive to anomalous behaviour.

For semi-local detection function $f(\cdot)$ a compressed representation of normal behaviour (the train data) is used. The residual between this model behaviour and the test data is computed. If the compressed representation of the measurements z_i exceeds the threshold $t_i = \mu_i + \sigma_i$ in any dimension, an outlier score $o_i = z_i - t_i$ is transmitted to the central detector. The final decision is then made based on the max-combiner rule. That is, the maximum value of outlier scores as transmitted by all semi-local detectors at timestep t, is taken as output for timestep t.

To put the attained performance into perspective, we implemented a baseline similar to the setup as proposed, but using data-dependent compression technique PCA instead. To analyse the detection performance of the two approaches, the Area Under the ROC Curve (AUC) is computed and averaged over 100 runs. This metric reflects the balance between correct detections and false alarms independent of the final decision threshold [10]. The detection performance of both approaches for the compression dimensionality d ranging from 1 to 6 are shown in figure 2a. Aside from detection performance, computational speed is considered an important metric. We have measured the runtimes of both approaches in Matlab, but runtime analysis will be conducted in a later phase of this research. Figure 2b shows the average runtime over 100 runs for the same range for the compression dimensionality.



(a) Detection performance (b) Runtime performance

Figure 2: Performance comparison of the approach using random projections and baseline with PCA.

From figure 2 it can be concluded that the random projection method and the PCA-based baseline are competitive in detection performance (taken $d = 2$ for random projections and $d = 3$ for PCA). However, if the runtime performance is taken into account, the advantage of the proposed approach becomes clear as this data-independent approach to data compression is significantly faster.

3.3 Analysis

One of the objectives is to provide theoretical insights in the performance and limitations of this approach. We are in the position to derive some performance properties (like compression runtime and error) analytically, as the compression technique based on random projections is independent of the intrinsic structure of the data. Furthermore, we aim to compare this approach in communication costs analytically with concurrent distributed approaches to fault detection.

As time is critical when it comes to fault detection, the objective is to detect a fault as soon as possible preferably even in a preliminary stage of failure. Detecting a fault at the time it is near or has just appeared is of more value than detecting the fault at the time it has affected the entire system already. Therefore, asymmetric evaluation functions to assess methods accordingly as proposed in [11], [12] and [13] will be studied.

Concluding, thorough numerical experiments should reveal additional advantages and limitations of our method. Experiments will be run on synthetic data sets such that interesting edge-cases can be assessed. Furthermore, a real-world data set will be used to evaluate the performance in a realistic context. This data set will also be used to numerically evaluate the competitiveness of the approach. To do so, we will implement at least one of the state-of-the-art approaches.

3.4 Implications of research

The outcome of the project would directly introduce a promising distributed fault detection architecture enhancing the field in multivariate ways, indicating its intellectual merit. The approach would lower the computational burden of signal compression, while attaining a competitive detection performance as illustrated by the preliminary experiments. Additionally, communication costs are expectedly lower than in concurrent distributed approaches as only coefficients are transmitted in case faults are suspected. Our distributed scheme would also enhance detection reliability as we can fall back on random, or structured, picking the output of one of the semi-local detectors. Furthermore, one of the research objectives is to explore the applicability of more advanced (supervised) ensemble learning techniques for outlier detection like stacking, bagging and boosting [14] to optimize detection performance. Such more advanced ensemble learning techniques have not been applied to the problem of fault detection often.

We also expect this research to have a broader impact. The application of random projections is well integrated in the field of Compressed Sensing [15]. However, it is not often used as a dimensionality reduction technique in the sense of compressing the number of features while maintaining the same number of measurements. As our preliminary experiments already illustrate, random projections are very convenient for dimensionality reduction in a high-dimensional feature space while not loosing much of the significance in the data. Therefore, we hope to reimburse the application of random projections as a dimensionality reduction technique in a wide area of scientific fields coping with high-dimensional feature spaces.

4 Research plan

To conduct this research successfully, we consider the steps as shown in figure 3 important. The foremost barrier we envision to be encountered, is the potential absence of a suitable real-world labelled data set in our evaluation phase. However, we will early and actively seek for advice on obtaining suitable labelled evaluation data from research experts within related disciplines. Due to the interdisciplinary nature of the research, we will also seek for discussion and feedback sessions with experts active in distributed (sensor) signal processing and fault detection, beside experts within our root-department of Pattern Recognition.

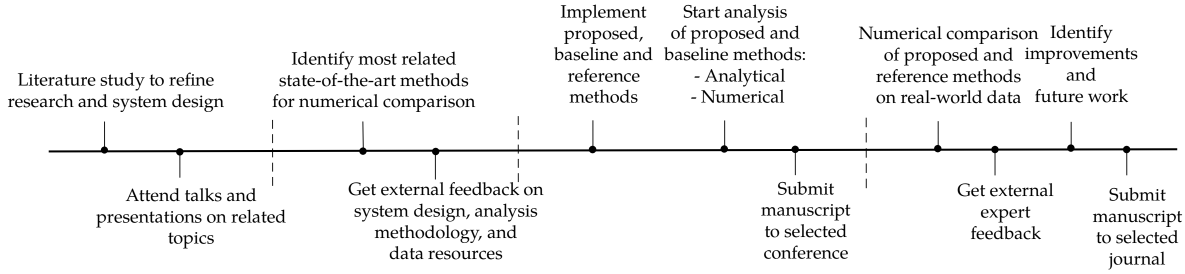


Figure 3: Timeline of the proposed resarch

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