Data-Driven Robot Fault Detection and Diagnosis Using Generative Models: A Modified SFDD Algorithm

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Short Summary

We present a modification of the correlation-based monitoring method in [1], replacing the manually specified modes with *learned models of pairwise sliding window correlations*. We particularly learn a probability distribution of *nominal* sliding window correlations between *the measurements of correlated sensor pairs*, where each such distribution is represented by a *generative model* (in particular, a Restricted Boltzmann Machine [2]). Violations of the learned dependencies are then used as an input in a subsequent diagnosis step.

Anomaly Detection Using Generative Models

Given: Sequence $\mathbf{c}$ of *sliding window correlations* between two system variables

$$\mathbf{c} = \{c_1, c_2, ..., c_n\}$$

Assumption: $\mathbf{c}$ follows an unknown density f with some additive noise ϵ

$$\mathbf{c} \sim f(\cdot) + \epsilon$$

Objective: Learn a model M that represents the unknown data distribution f describing the *nominal measurements*.

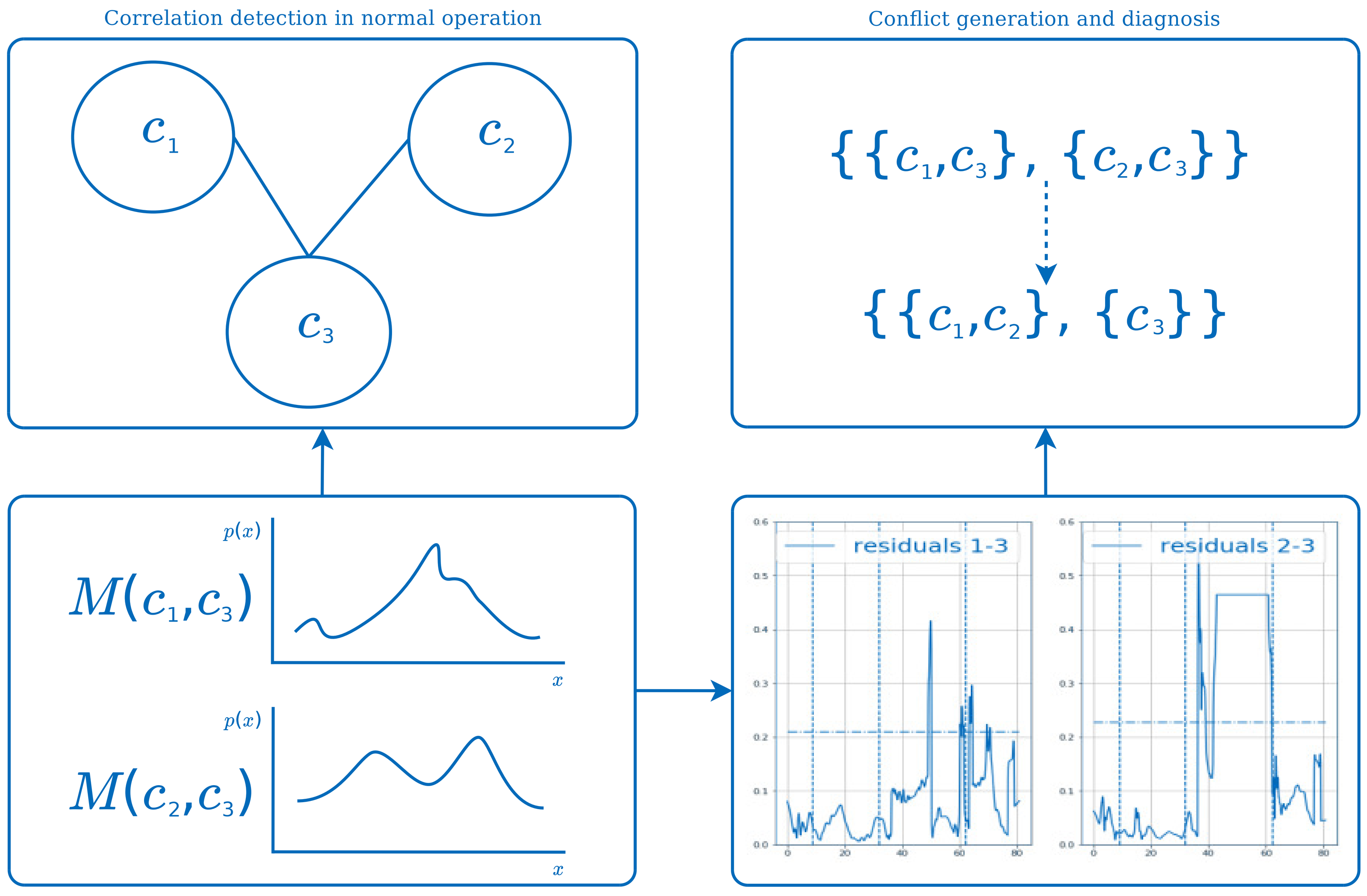
Why? To detect anomalies: Given a dissimilarity measure d and a sample $\mathbf{m}$ drawn from M, we calculate a residual as

$$r = d(\mathbf{c}_{t-k,t}, \mathbf{m})$$

and, using a predefined threshold δ, we can classify $\mathbf{c}_{t-k,t}$ as

$$\begin{cases} \text{nominal, if } r \leq \delta \\ \text{faulty} \quad \text{otherwise} \end{cases}$$

FDD Using Learned Dependency Models



1. Identifying Correlated Sensor Pairs

As in [1], we monitor a set C of *correlated sensors*

$$C = \{(S_i, S_j) \mid 1 \leq i, j \leq m, i \neq j, \text{corr}(S_i, S_j) = 1\}$$

such that we identify correlated sensors in an offline data set of nominal measurements using a modified Pearson correlation coefficient:

$$\rho(\mathbf{x}, \mathbf{y}) = \begin{cases} \frac{\text{cov}(\mathbf{x},\mathbf{y})}{\sigma_i \sigma_j}, & \sigma_i, \sigma_j > 0 \\ 1, & \sigma_i, \sigma_j = 0 \\ 0, & \sigma_i = 0 \text{ xor } \sigma_j = 0 \end{cases} \qquad \text{corr}(S_i, S_j) = \begin{cases} 1, & \rho_{S_i,S_j} = \rho(\mathbf{x}_i, \mathbf{x}_j) > \kappa \\ 0 & \text{otherwise} \end{cases}$$

2. Learning Dependency Models

Given C, we learn a generative dependency model $M_{i,j}$ for each pair of correlated sensors S_i and S_j.

We encode the dependency between two sensors by the correlation between sliding windows extracted from $\mathbf{x}_i$ and $\mathbf{x}_j$ (the measurements of sensors S_i and S_j).

The model learning process is performed in an offline fashion, such that *each $M_{i,j}$ encodes the distribution of the nominal dependency state between S_i and S_j.*

3. Anomaly Detection

After learning $M_{i,j}$, we calculate a threshold $\delta_{i,j}$ as

$$\delta_{i,j} = \mu_{i,j} + w\sigma_{i,j}$$

where $\mu_{i,j}$ is the mean residual on the training measurements, $\sigma_{i,j}$ is the standard deviation of the training residuals, and w is a multiple of the standard deviation.

During online operation, we generate a sample $\mathbf{m_{i,j}}$ given the current input, calculate a residual r, decide on the nominality, and, if necessary, perform subsequent diagnosis.

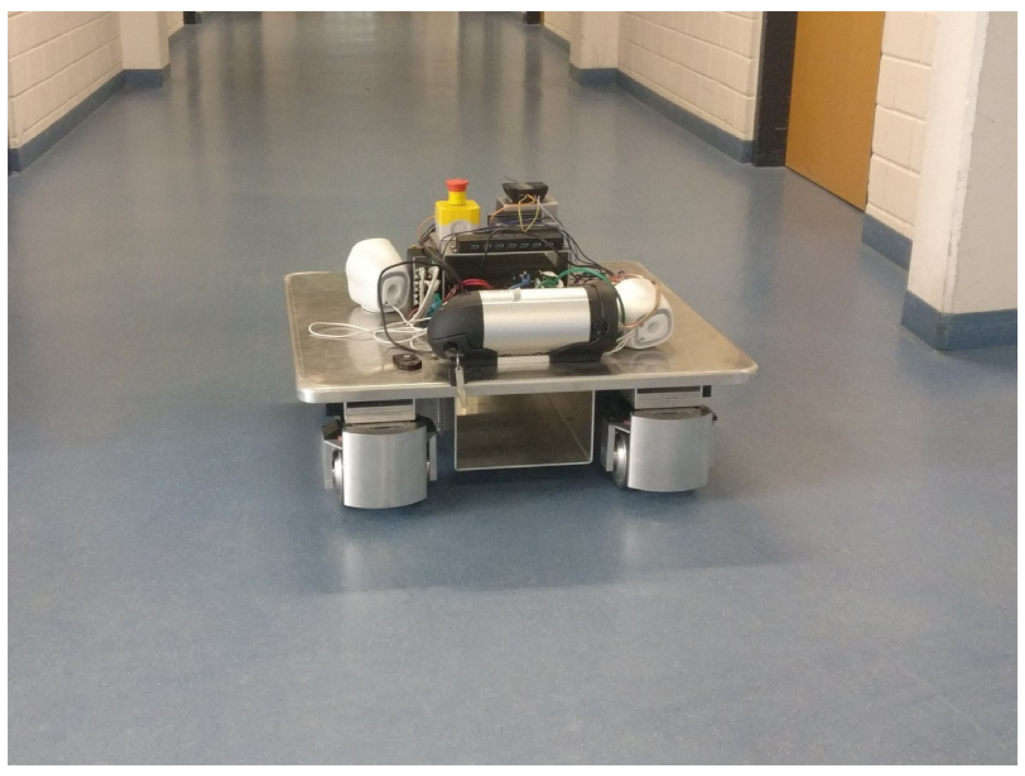
4. Fault Diagnosis

If a dependency violation is detected, a fault diagnosis step is performed.

In particular, we create a conflict set for each of pair of components S_i and S_j for which $r_{i,j}$ exceeds $\delta_{i,j}$; this gives rise to a collection of conflict sets CS.

Given CS, we apply the HS-DAG algorithm for finding diagnoses using the implementation by Quaritsch and Pill [3].

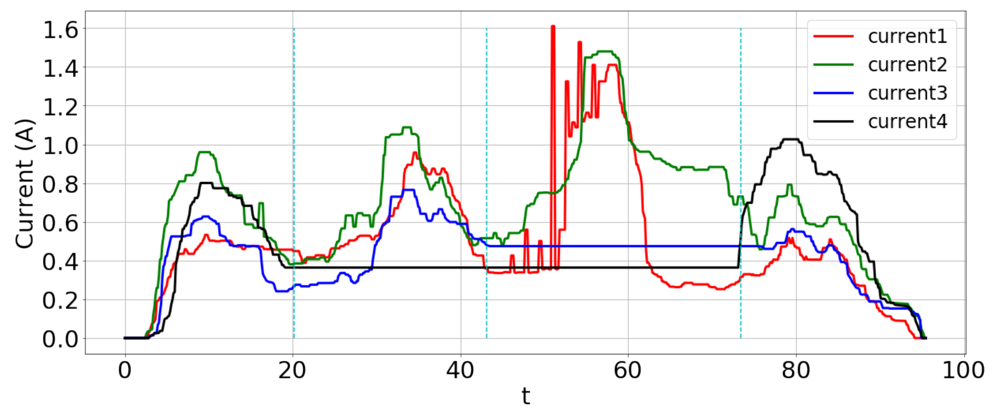
Experimental Evaluation: Lost Communication With Wheels



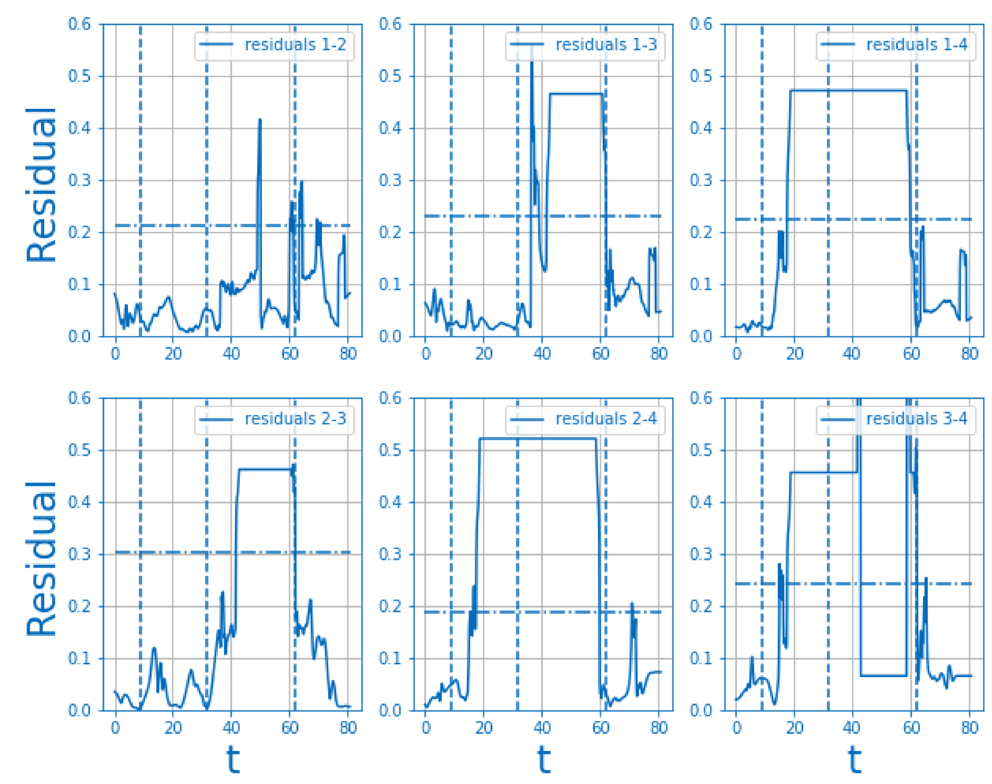
Test platform: Four-wheel omnidirectional robot

We verify the operation of the method by manually injecting a fault (disconnected communication cables) to a ROPOD platform (a hospital logistics robot) [4]

Anomalies are detected by monitoring the current measurements of the individual wheels (which are correlated)



Current measurements with introduced faults



Correlation residuals on the faulty data

Future Work

- Using a context transition and, when necessary, recognition model for applying dedicated models in different operating modes
- Extending the diagnosis module for higher-level execution failures
- A more detailed metaparameter investigation (features other than Pearson correlation, different dissimilarity metrics)
- Application to different robots (Toyota HSR, KINOVA KORTEX Gen3)

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