Cognitive Fault Detection and Diagnosis in Sensor-based Embedded Systems

Intelligence for Embedded Systems

Ph. D. and Master Course

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Inspect natural environments, CISs or cyber-physical systems by providing:

\[
X(t) = \begin{bmatrix}
x_1(t) \\
\vdots \\
x_n(t)
\end{bmatrix} \in \mathbb{R}^n
\]

\(X(t)\) are analysed for the purposes of the considered application to make decisions/activate reactions.

Sensor networks suffer from faults, ageing effects or thermal drifts in the embedded electronics or the sensors.
Fault Detection and Diagnosis Systems

Specific tasks:
- **Detection**: perceive as soon as possible if a change has occurred
- **Isolation**: locate the sensor (or unit) where the fault has occurred
- **Identification**: gather information about the nature of the fault (e.g., magnitude, type)

In addition:
*We want to understand if the change is due to a change in the environment or a fault in the sensors of the embedded system*
Traditional Fault Detection mechanisms

- **Operating principle**: on-line comparison of the actual system observed behaviour against the known “normal operation behaviour”.

  ![Diagram](image)

- **Knowledge about the “normal operation behaviour”**:  
  - Empirical knowledge  
  - Extracted from data  
  - Physical modelling
Fault diagnosis (identification and isolation) relies on comparing the observed behaviour of the monitored system with the a-priori knowledge about it.

Remarks:

- Real-time operation.
- Knowledge for normal and faulty operations is needed (knowledge about normal operation is enough for FD)
- All faults have to affect the observed variables (detectable faults) in a different way (isolable faults).
From Traditional Fault Detection and Diagnosis to Cognitive Approaches

<table>
<thead>
<tr>
<th>Fault Detection and Diagnosis Systems</th>
<th>Cognitive Fault Detection and Diagnosis Systems</th>
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<tr>
<td>These systems consider techniques from several fields (e.g., automatic control, machine learning)</td>
<td>Overcome traditional assumptions</td>
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<td>Traditional systems generally require:</td>
<td>Able to automatically characterize the nominal state and the faults, by analyzing the spatial and temporal redundancies existing among provided data</td>
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<tr>
<td>• information about the process</td>
<td>Active field since existing CFDDDS are:</td>
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<tr>
<td>• information about the faults</td>
<td>• application specific</td>
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<tr>
<td>• information about uncertainties</td>
<td>• limited to a single aspect of fault detection and diagnosis</td>
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Different sensors have different views of the same phenomenon

We want to exploit the causality of the phenomenon reflected by the sensor network
Cognitive Fault Diagnosis in Sensor Networks

- Fault Dictionary
- Cognitive Fault Identification
- Cognitive Fault Isolation
- Cognitive Fault Detection
- Dependency Graph Learning

Diagram:

1. $s_1$
2. $s_2$
3. $s_3$
4. $s_4$
5. $s_5$
6. $s_6$

Dependency arrows indicate relationships between sensor nodes.
A General Architecture for CFDDDS

- System Characterization
  - Fault Dictionary
  - Dependency Graph
  - Nominal State

- Learning
  - Fault Identification
  - Cognitive Fault Isolation
  - Cognitive Fault Detection

- $\theta_1, \ldots, \theta_t$
1) Dependency Graph Learning Phase

System Characterization

Dependency Graph

θ₁, …, θₜ

Learning

Temperature (°C)

Sensor 1
Sensor 2
Sensor 3
Algorithm based on a theoretically-grounded statistical test to evaluate the dependency between data streams.

Considers the Multivariate Conditioned Granger Causality.

\[
\mathcal{M}_f^{(t)} : x_i(t) = \sum_{k=1}^{\tau} \sum_{h=1}^{n} a_{ihk} x_h(t - k),
\]

\[
\mathcal{M}_{r}^{(ij)} : x_i(t) = \sum_{k=1}^{\tau} \sum_{h=1, h \neq j}^{n} a'_{ihk} x_h(t - k),
\]
2) Cognitive Fault Detection Phase

System Characterization

Nominal State

Dependency Graph

Learning

Cognitive Fault Detection

\[ \theta_1, \ldots, \theta_t \]
Cognitive Fault Detection Phase

Traditional solutions

<table>
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<th>Fault Detection</th>
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<tr>
<td>• Data driven approaches</td>
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<tr>
<td>• Signal-based techniques</td>
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<tr>
<td>• Model-based methods</td>
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<tr>
<td>• <strong>Cognitive change detection methods</strong></td>
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Cognitive solutions

<table>
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<th>Cognitive Fault Detection</th>
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<tr>
<td>• ICI-based CDT</td>
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<td>• HMM-CDT</td>
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<td>• Ensemble of HMM-CDT</td>
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Require a priori information on the system or on the faults
ICI-based Change Detection Test

Fault detection action: a change detection test on $e(t)$

The ICI-based CDT assesses the stationary of $e(t)$ over time
Fault Detection and Diagnosis in Parameter Space

Each edge in the dependency graph models a functional constraint between a couple of sensors

\[ f_{(i,j)}(t, \theta, x_j(t-1), \ldots, x_j(t-\tau_j), x_i(t), \ldots, x_i(t-\tau_i+1)) \]

Each functional relationship is approximated with a Linear Time Invariant (LTI) model and analyze the statistical behaviour of the LTI estimated parameter \( \hat{\theta} \)

Under weak assumptions over the functional relationship and the estimation process (Ljung):

\[
\lim_{{N \to \infty}} \sqrt{N} \sum_{{N}}^{-\frac{1}{2}} (\hat{\theta} - \theta^o) \sim \mathcal{N}(0, I_p)
\]

Theoretical justification to consider a Gaussian topology of the parameter space
HMM-based Change Detection Test

**Sensing Unit**

\[ y_1(t) \rightarrow f_{\theta}^{1,2} \rightarrow y_2(t) \]

**Estimate the model parameters** \( \hat{\theta}_t \)

**Operational phase**

\[ \hat{\theta}_t, \ldots, \hat{\theta}_n \]

**Fault detection action:**
model the statistical behavior the \( \hat{\theta}_t \) s by means of HMM

If the likelihood of the HMM decreases below a threshold, a change in the relationship is detected.
Cognitive Fault Detection: Ensemble Approach to HMM-based Analysis

Nominal State

Ensemble of HMMs trained over the parameter vectors

$$\Theta_L = (\hat{\theta}_1, \ldots, \hat{\theta}_L)$$

Fault Detection

Evaluate the discrepancy of

$$\Theta_{t,k} = (\hat{\theta}_{t-k+1}, \ldots, \hat{\theta}_t)$$

by computing the HMMs loglikelihoods

Algorithm 3 EHAMM-CDT algorithm

1. Data: $C_D$; $C_{T^*}$; $C_{S^*}$; $C_{P^*}$; $C_N$; $C_D$; $C_{DP}$; $C_{D^*P}$; $C_{D^*P^*}$; $C_{N^*}$; $C_{D^*N}$; $C_{D^*N^*}$; $C_{D^*P^*N}$; $C_{D^*P^*N^*}$; $C_{D^*P^*N^*}$; $C_{D^*P^*N^*}$
2. Result
3. Estimate $\hat{\theta}$ using $\hat{\theta}_{L,M}$ by considering a random initialization point.
4. for $i \in \{1, \ldots, O\}$ do
5.   Estimate HMM $H_i$ using $\Theta_{L,M}$
6. end for
7. Built the ensemble $E = \{H_1, \ldots, H_O\}$
8. for $h \in \{M + k, \ldots, O\}$ do
9.   for $i \in \{1, \ldots, e\}$ do
10.      Compute $l(H_i, \Theta_{L,M})$
11. end for
12. Compute $A(h) = A(l(H_1, \Theta_{L,M}), \ldots, l(H_e, \Theta_{L,M}))$
13. end for
14. Compute $T$
15. while a new couple $[x_i(t), x_j(t)]$ is available at time $t$ do
16.   Estimate $\hat{\theta}_i$ by using $Z_{N,M}$
17.   Built the sequence $\Theta_{k,i}$
18.   for $i \in \{1, \ldots, e\}$ do
19.      Compute $l(H_i, \Theta_{k,i})$
20. end for
21. Compute $A(t) = A(l(H_1, \Theta_{k,i}), \ldots, l(H_e, \Theta_{k,i}))$
22. if $A(t) \leq T$ then
23.    return $T \leftarrow t$
24. end if
25. end while
26. return $T \leftarrow \emptyset$
3) Cognitive Fault Isolation Phase
Cognitive Fault Isolation

Given a detection on \( f_{(3,2)} \)

We consider the HMM loglikelihoods on different group of relationships

Fault in \( S_2 \)

Fault in \( S_3 \)

Change in the environment

Logic partition of the dependency graph
4) Cognitive Fault Identification Phase

- System Characterization
  - Fault Dictionary
  - Dependency Graph
  - Nominal State

- Learning

- Fault Identification
- Cognitive Fault Isolation
- Cognitive Fault Detection

\[ \theta_1, \ldots, \theta_t \]
Evolving Clustering in Parameter Space

\[ \theta \]

\[ \Phi_1 \text{ faulty cluster} \]

\[ \Psi_1 \text{ nominal cluster} \]

\[ \Phi_2 \text{ faulty cluster} \]

\[ \Theta_1 \]

\[ \Theta_2 \]

O Outlier set

Algorithm 4: Evolving Clustering-Based Identification Algorithm

1: Data: Training set \( Z_{n\times l}^{(i)} \); \( \alpha_s, \sigma_n, \eta \);
2: Results: Nominal cluster \( \Psi \), Fault dictionary \( \Phi \);
3: Compute mean \( \bar{\theta} \) and covariance matrix \( S_\theta \) for the nominal state cluster
4: Set \( n_\Psi = L \) and \( t_\Psi = L \).
5: Set \( \Phi = \emptyset \) (\( n = 0 \)) and \( O = \emptyset \);
6: while A new \( \bar{\theta} \) is available do
7: if the spatial condition holds \( \Psi \) then
8: Associate \( \bar{\theta} \) to \( \Psi \);
9: if \( |t_\Psi - i| \leq \eta \) then
10: \( \bar{\theta} \) to \( \Psi \);
11: end if
12: \( t_\Psi \leftarrow i \);
13: else
14: if \( \Phi \neq 0 \) and the spatial condition holds for at least one \( \Phi_j \in \Phi \) then
15: Select \( \Phi \) minimizing the Mahalanobis distance;
16: Associate \( \bar{\theta} \) to \( \Phi \);
17: end if
18: Update \( \Phi \);
19: for \( \bar{\theta} \in O \) do
20: if the spatial condition holds for \( \Phi \) then
21: Remove \( \bar{\theta} \) from outlier set \( O \);
22: Associate \( \bar{\theta} \) to \( \Phi \);
23: if \( |t_\Phi - i| \leq \eta \) then
24: Update \( \Phi \);
25: end if
26: end if
27: end for
28: for \( \Phi_j \in \Phi, \Phi \neq \Phi \) do
29: if the merging conditions hold for \( \Phi \), \( \Phi_j \) then
30: Merge \( \Phi \), \( \Phi_j \);
31: end if
32: end for
33: end if
34: \( t_\Phi \leftarrow i \);
35: if \( \Phi = \emptyset \) then
36: Insert \( \bar{\theta} \) in \( O \);
37: Create \( O \) according to cluster creation algorithm
38: if \( O \neq \emptyset \) then
39: \( \hat{\theta} \leftarrow \Phi \);\n40: Create \( \Phi \) using \( \hat{\theta} \in O \);
41: end if
42: end if
43: end if
44: end while
Example of CFDDS Identification phase
Identification Algorithm Key Points

Parameter insertion in clusters

\[
m(\theta, \Upsilon_{j^*}) \leq \frac{(v_j^2 - 1)p}{v_j^* (v_j^* - p)} F_{p,v_j^*-p,\alpha_z} \]

\[
\frac{v}{v+1} m(\theta, \Upsilon) \sim \frac{(v-1)p}{(v-p)} F_{p,v-p}
\]

Cluster merging

\[
m(\widetilde{\Theta}_j, \Upsilon_k) \leq \frac{(v_k + 1)(v_j - 1)p}{v_j (v_kv_j - v_k - p + 1)} F_{p,v_k v_j - v_k - p + 1, \frac{\alpha_{m}}{2}}
\]

\[
m(\widetilde{\Theta}_k, \Upsilon_j) \leq \frac{(v_j + 1)(v_k - 1)p}{v_k (v_j v_k - v_j - p + 1)} F_{p,v_j v_k - v_j - p + 1, \frac{\alpha_{m}}{2}}
\]

\[
\frac{v'^v}{v'^{v+1}} m(\Theta, \Upsilon') \sim \frac{v'(v-1)p}{(v'v - v' - p + 1)} F_{p,v'v-v'-p+1}
\]

Cluster creation

Joint spatial-temporal norm

\[
\|\theta\|_w^2 = w \sum_{j=1}^{p} (\theta_j)^2 \frac{1}{2p} + (1 - w) \frac{1}{i_c}
\]

Kolmogorov-Smirnov test

\[
H_0 : \hat{F} = F_\Gamma \text{ vs. } H_1 : \hat{F} \neq F_\Gamma
\]

\[
D^p = \max_{0 \leq \alpha \leq 1} |\hat{F}(B_\alpha) - F_\Gamma(B_\alpha)|
\]
Applicative Scenario: Environmental Monitoring of Rock Collapse and Landslide

Rialba Towers rock collapse and landslide forecasting system
Complex system even if the physical model of its parts are known

The isolation is fundamental for prompt maintenance of the system
FDDSs based on the **cognitive approach** are able to cover all the phases of fault detection and diagnosis in the sensor-based networked embedded scenario.

These systems exploit the temporal and spatial relationship existing among data with the dependency graph, to characterize the nominal state of the inspected system and to **learn the fault dictionary** during the operational life of the system, without requiring a priori information.