Distributed Fault Detection and Identification for Interdependent Infrastructures

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We Live in a Distributed World!!

- Naturally, we live in a distributed world
- Networks, nodes, interdependencies, flows, interconnected systems, etc.
- Directly and indirectly interconnected systems
- Centralized vs. Distributed decision making
- Distributed decision making is natural in a distributed world
- Communication plays a key role in distributed decision making
- Balance between optimizing “local” objectives and “global” objectives
Distributed Decision and Control Applications

- Distributed Autonomous Vehicles
- Military and Security Applications
- Chemical and Petrochemical Engineering Processes
- Biomedical Engineering Applications
- Environmental Monitoring and Control Applications
- Critical Infrastructure Systems
Critical Infrastructure Systems

- Power systems
- Telecommunication networks
- Water systems (clean water and wastewater)
- Transportation systems

→ Interdependent systems that work together to provide the essential services of a modern society
Critical Infrastructure Systems (CIS) are crucial for everyday life and well-being

- Citizens expect/rely that CIS will *always* be available (24/7).
- Citizens expect that they will be managed *efficiently* (low cost).

Critical infrastructure systems do fail

- Natural disasters (earthquakes, flooding)
- Accidental failures (equipment failures, human error, software bugs)
- Malicious attacks (directly, remotely)

When critical infrastructures fail the consequences are tremendous

- Societal consequences
- Health hazards
- Economic effects
The problem of managing Critical Infrastructure Systems is expected to get more difficult

- CIS were not designed to be so large - they evolved due to growing demand
- Deregulation has resulted in more heterogeneous and distributed infrastructures, which make them more vulnerable to failures and attacks
- Renewables and environmental issues present new challenges
- There are more and more interdependencies between CIS
- Fewer people understand how these networks work and the interactions between all the components
- There are no reliable models that can predict their behavior under all the various scenarios
- Mega-cities: 18 in 2000, estimated 30 by 2020, 60 by 2050 → leading to the Smart Cities initiatives.
Motivation for Fault Diagnosis

• Technological advances in sensor/actuator networks, wireless communications and real-time software
• Sophisticated monitoring and control applications
• Huge data of different characteristics (in time and space) - moving to big data environments
• Advanced data processing and automated decision making

• However, data may be faulty, inconsistent or missing (nonsense data)
• Faulty data may result in wrong decisions or escalation to a failure
Faulty Scenarios in Uncertain Dynamical Systems

- Process Faults
- Actuator Faults
- Sensor Faults
- Communication Faults
- Controller Faults
- Malicious Attacks (cyber-security)
Motivation for Fault Diagnosis

→ **Need for intelligent data processing methods for:**
  - fault detection
  - fault isolation
  - fault identification and risk assessment
  - fault accommodation

→ **Need for cognitive fault diagnosis approaches to:**
  - learn characteristics or system dynamics
  - adapt to unforeseen scenarios
  - predict missing or inconsistent data
  - exploit spatial and temporal correlations between variables
  - prevent “small” fault events from escalating into a major failure
General Centralized Architecture

Control Algorithm

Fault Accommodation

Fault Monitoring And Diagnosis

Supervisory Algorithm

Controller

Plant

r → u → d → f → y
Distributed Fault Diagnosis Architecture
Distributed-Hierarchical Fault Diagnosis

RFD/RFI Agent

LFD/LFI Agent

LFD/LFI Agent

LFD/LFI Agent

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Fault Diagnosis in Cyber-Physical Systems
Example: Water Distribution Networks

**Objective:** control the spatio-temporal distribution of drinking water disinfectant throughout the network by the injection of appropriate amount of disinfectant at suitably chosen actuator locations.
Problem Formulation

$$\dot{x}_i = \phi_i(x_i, u_i) + \eta_i(x_i, u_i, t) + \mathcal{B}(t - T_0) f_i(x_i, u_i) + \sum_{j \in \mathcal{J}} h_{ij}(x_j)$$

where:

- \(x \in \mathbb{R}^n\): state vector
- \(u \in \mathbb{R}^m\): input vector
- \(\phi : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n\): Nominal state dynamics
- \(\eta : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^+ \rightarrow \mathbb{R}^n\): Modeling uncertainty
- \(f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n\): Change in the system due to fault
- \(\mathcal{B}(t - T_0)\): Time profile of the fault
- \(h_{ij}(x_j)\): Interconnection dynamics
The modeling uncertainty $\eta$ includes external disturbances as well as modeling errors.

$$|\eta_i(x, u, t)| \leq \bar{\eta}_i(x, u, t), \quad \forall (x, u) \in \bar{D}, \quad \forall t \geq 0,$$

where for each $i = 1, \ldots, n$, the bounding function $\bar{\eta}_i(x, u, t) > 0$ is known, integrable and bounded for all $(x, u)$ in some compact region of interest $\bar{D} \supseteq D$.

The handling of the modeling uncertainty is a key design issue in fault diagnosis architectures:
- need to distinguish between faults and modeling uncertainty
- structured vs. unstructured modeling uncertainty
- trade-off between false alarms and conservative fault detection schemes
The term $\mathcal{B}(t - T_0) f(x, u)$ represents the deviations in the dynamics of the system due to a fault.

- $f(x, u)$ is the fault function
- The matrix $\mathcal{B}(t - T_0)$ characterizes the time profile of a fault which occurs at some unknown time $T_0$

$$\mathcal{B}(t - T_0) = \text{diag} \left[ \beta_1(t - T_0), \ldots, \beta_n(t - T_0) \right]$$

$$\beta_i(t - T_0) = \begin{cases} 
0 & \text{if } t < T_0 \\
1 & \text{if } t \geq T_0
\end{cases}$$

for $\text{abrupt}$

$$\beta_i(t - T_0) = \begin{cases} 
0 & \text{if } t < T_0 \\
1 - e^{-\alpha_i(t - T_0)} & \text{if } t \geq T_0
\end{cases}$$

for $\text{incipient}$

where $\alpha_i > 0$ denotes the unknown fault evolution rate.
Fault Influence for Distributed Systems

- Local Faults
- Distributed Faults
- Propagating Faults
Fault Detection and Approximation Estimator

\[ \dot{x}^0 = -\Lambda^0 (\tilde{x}^0 - x) + \phi(x, u) + \hat{f}(x, u, \hat{\theta}^0) \]

where:
- \( \tilde{x}^0 \in \mathbb{R}^n \): estimated state vector
- \( \hat{f} : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \mapsto \mathbb{R}^n \): Adaptive approximation model
- \( \hat{\theta}^0 \in \mathbb{R}^p \): adjustable weights of the on-line neural approximator
- \( \Lambda^0 = \text{diag}(\lambda_1^0, \cdots, \lambda_n^0) \): estimation poles

- The initial weight vector \( \hat{\theta}^0(0) \) is chosen such that
  \[ \hat{f}(x, u, \hat{\theta}^0(0)) = 0, \quad \forall (x, u) \in \mathcal{D} \quad \text{(healthy situation)} \]
Adaptive Approximation Model

- Nonlinear approximation model with adjustable parameters (e.g., neural networks)
- Linearly parameterized vs. nonlinearly parameterized
- It provides the adaptive structure for approximating online:
  - Local modeling errors
  - Interconnection dynamics
  - Unknown fault functions
Learning Algorithm

\[ \hat{\theta}^0 = \mathcal{P}_{\Theta^0} \left\{ \Gamma^0 Z^\top D[\epsilon^0] \right\} \]

where:

\[ \epsilon^0 = x - \hat{x}^0 : \text{state estimation error} \]

The projection operator \( \mathcal{P}_{\Theta^0} \) restricts the parameter estimation vector to a predefined compact and convex region.

\[ Z = \frac{\partial \tilde{f}(x, u, \hat{\theta}^0)}{\partial \hat{\theta}^0} : \text{regressor matrix} \]

\[ \Gamma^0 = \Gamma^0 \top \in \mathbb{R}^{p \times p} : \text{Positive definite learning rate matrix} \]

\[ D[\epsilon^0(t)] = \begin{cases} 0 & \text{if } |\epsilon^0_i(t)| \leq \tilde{\epsilon}^0_i(t), i = 1, \ldots, n \\ \epsilon^0(t) & \text{otherwise} \end{cases} \]

Dead-zone operator
Further Fault Diagnosis Topics

- Multiple Sensor Fault Detection and Isolation
- Fault Accommodation of Large-Scale Interconnected Nonlinear Systems
- Filtering Approach for Distributed fault Diagnosis
- Coordinated Communication for Distributed Fault Tolerant Control
- Security-Oriented Sensor Placement
- Applications in various domains
Performance Evaluation of Fault Diagnosis

- Robustness (false positives)
- Detectability Analysis (false negatives)
- Fault Detection Time
- Fault Isolability
- Stability Analysis
- Learning Characteristics
- Fault Accommodation Properties
Fault Diagnosis and Security

- Targeted faults
- Early detection is crucial
- Sensor placement is a key issue
- Need to consider the impact dynamics
Key Research Issues

- Development of suitable architectures
  - Distributed; Decentralized; Hierarchical
- Communication and cooperation between intelligent agents
  - How much communication is needed?
  - Event-based communication
- Development of hardware devices
  - Cost
  - Size
  - Reliability
  - Energy efficiency
- Development of algorithms for real-time information processing
- Intelligent decision support systems
Concluding Remarks

- Distributed fault diagnosis is a key area of growth
- Fault Diagnosis will play a key role in Big Data computing
- Distributed fault diagnosis of complex large-scale systems and cyber-physical systems
- Trend towards more sensors but cheaper sensors → more susceptible to faults
- Need for intelligent software to address faulty behavior of hardware