Modeling and Analysis of Cyber-Physical Manufacturing Systems for Anomaly Detection

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Challenges of anomaly detection

• **Process variability and dynamics:** Combination of transient and steady state operation [1]

• **Part interaction:** Changing loads due to different machine-part interactions

• **Data collection:** Cost and access constraints

Cyber-Physical Manufacturing Systems

SUPPORT INTEGRATED ANALYSIS OF COMPLEX PROCESSES

Intro
CPS
Approach
Case1
Case2
Case3
Conclusion

DeviceNet
Ethernet/IP
Internet of Things (IoT)

Physical

Network

Software

Sensors data
Dynamic models
Part information

Control logic
Commands
Algorithms

Objective

Improve anomaly detection and diagnosis in manufacturing processes

Solution:[3]

- Model Cyber-Physical Systems considering both, Cyber and Physical domains
- Context-specific analysis of manufacturing operation merging multiple models

Identify Operational Context

Global Operational State (GOS):
- **Functional**: Reduced controller model
- **Dynamic**: States describing machine dynamics
- **Interactive**: Describe the operations in the part
- **Information**: Explicit process descriptors

\[
G = [Y(1) \ldots Y(m)]^T
\]

\[
e^I = [Y_{ref}(1) \ldots Y_{ref}(n)]^T
\]

\[
\min(DTW(e^I, G))
\]
Define Context-Specific Model

- **Multi-model Specification:** \[ M = (GOS, U, X, Y, F, H) \]

  - \( GOS \): Global Operational State
  - \( U \): Continuous inputs
  - \( X \): State variables
  - \( Y \): Output variables
  - \( F \): Mapping of state variable functions
  - \( H \): Mapping of output variable functions

- **Adaptive Threshold Limits:**
  \[ \Delta r_{GOS} = \mu \pm \psi_R Z \sigma \]

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Case Study: Conveyor

- Available controller data

<table>
<thead>
<tr>
<th>Type</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Categorical</td>
<td>Vehicle model</td>
</tr>
<tr>
<td>Functional state</td>
<td>Ready, Processing, Down</td>
</tr>
<tr>
<td>State-space</td>
<td>Velocity, Torque</td>
</tr>
<tr>
<td>Energy</td>
<td>Current, Voltage, Frequency</td>
</tr>
</tbody>
</table>
Case Study: Conveyor

Anomaly detection: Adaptive threshold limits

(Snapshot measurements)

<table>
<thead>
<tr>
<th>State</th>
<th>GOS₁</th>
<th>GOS₂</th>
<th>GOS₃</th>
<th>GOS₄</th>
<th>GOS₅</th>
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<tbody>
<tr>
<td>Dynamic</td>
<td>Accel</td>
<td>Accel</td>
<td>Const</td>
<td>Const</td>
<td>Const</td>
</tr>
<tr>
<td>Interactive</td>
<td>Part.Out Front/Rear</td>
<td>Part.Out Front</td>
<td>Part.Out Front</td>
<td>Part.In Rear</td>
<td>Part.In Front</td>
</tr>
</tbody>
</table>

- Limits
- Segments
- Current Sig. W/Backlash
Case Study: Conveyor

Anomaly diagnosis: Supervised learning (SVM) to separate Backlash from Good

Entire Signal - Classification Accuracy: 60.1%

GOS$_1$ - Classification Accuracy: 91.7%

Entire signal: 60%

Only GOS$_1$: 92%

32% IMPROVEMENT IN ROOT CAUSE DIAGNOSIS
Case Study: Conveyor

**Productivity analysis:** Monitoring time of sub-tasks

Mean increase in time in $\text{GOS}_4$ when wheels are worn

DETECT 0.6 SEC INCREASE IN SUB-TASKS TIME
Case Study: CNC Machine

- Merge sensor data and context information

Process step + Artificial vision + Controller model + Energy signature

G21
G90
G00 X143.135 Y107.226 S3500 M03
Z60.237
G03 X-.627 Y.627 Z0 I-.627 J0 K0
G00 X155 Y108.54
Case Study: CNC Machine

- Multi-Model Framework:

\[ \dot{I} = Jq + M_{F1} \dot{q} + M_{F0} \frac{\sin(\dot{q})}{\psi} \]

Single Mass dynamic model

\[ \phi_1(B) \dot{I} = \phi_{I1}(B)q + \phi_{I2}(B)\ddot{q} + \epsilon \]

Autoregressive model
Case Study: CNC Machine

- **Multi-Model Framework:**

<table>
<thead>
<tr>
<th>State</th>
<th>GOS 1</th>
<th>GOS 2</th>
<th>GOS 3</th>
<th>GOS 4</th>
<th>GOS 5</th>
<th>GOS 6</th>
<th>GOS 7</th>
<th>GOS 8</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dynamic</strong></td>
<td>2 in/sec</td>
<td>5 in/sec</td>
<td>50 in/sec</td>
<td>2 in/sec</td>
<td>2 in/sec</td>
<td>2 in/sec</td>
<td>50 in/sec</td>
<td>5 in/sec</td>
</tr>
<tr>
<td><strong>Interactive</strong></td>
<td>No Int.</td>
<td>Side Int.</td>
<td>No Int.</td>
<td>Side Int.</td>
<td>No Int.</td>
<td>End Int.</td>
<td>No Int.</td>
<td>Side Int.</td>
</tr>
</tbody>
</table>

DEFINE CONTEXT-SENSITIVE ADAPTIVE THRESHOLD LIMITS
Case Study: CNC Machine

Collect Raw data

Partition by part feature

Partition by Interaction

Extract Signal features

Context-Specific Classification Model

Intro CPS Approach Case1 Case2 Case3 Conclusion
Case Study: CNC Machine

Use supervised learning (SVM) to separate worn tool from wrong material.

Entire signal: 75%

Partition by part feature: 81.2%

Partition by part feature and GOS: 93.6%
Case Study: CNC Machine

Develop context-specific diagnosis rules:
• Extract context information
• Identify fault patterns
• Define classification rules

Diagnose tool breakage under different operational context

CONTEXT KNOWLEDGE CAN SIMPLIFY DIAGNOSIS
Case Study: Electro-Pneumatic Systems

Common automation applications:

Examples:
- Welding fixtures
- Gantry systems
- Assembly stations

Approach:
- Monitor data from:
  - Position sensors
  - Pressure and flowmeters
- Study discrete states
Case Study: Electro-Pneumatic Systems

Merge sensor data and controller model to detect leaks in multiple location and sizes.
Cyber-Physical Manufacturing Systems

- Worn components
- Backlash
- Worn/Broken tool
- Damaged fixture
- Wrong part
- Leaks
- Joint problems
- Wrong trajectory
Conclusion

• Merging sensor data with context information help to understand the machine operational context

• Feature extraction of a non-stationary signal can be improved by adding information of the cyber domain

• Modeling requires merging expert knowledge and machine data into process analysis algorithms

Thanks