Condition Monitoring auf Basis statistischer, semantischer und hybrider Signalverarbeitung – Projekt ICM-Hydraulik

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Introduction

Project Objectives
ICM-Hydraulic System Innovations
Intelligent Condition Monitoring

- Condition-based maintenance requires human experts to interpret complex interdependencies between measured sensor data and system conditions.

**CM Automation Challenges**

- Knowledge-based *explanation* of detected faults to experts and non-experts
- Fast *quantitative and qualitative reasoning* on sensor data for fault detection and diagnosis
- *Adaptation* to different hydraulic systems
iCM-Hydraulic

- Combines statistic and semantic technologies to detect and diagnose probable faults with user understandable explanation

- Configuration: 2 hydraulic test benches, 17 sensors, 1 min working cycle
- Performance: 50k obs/min per bench (throughput)
- Fast offline and online analysis

Mobile client for monitoring hydraulic test benches

Information on probability and symptom states for Pump’s ‘Poor’ condition. “Diagnose” details possible causes of fault and condition.
Statistical Fault Classification

Concept of automated statistical analysis
Component fault detection
(Sensor fault detection and compensation)
Statistical Analysis Overview

- **Sensor data**
  - Raw data

- **Feature extraction**
  - sensor
  - section
  - feature
  - Feature Pool
  - 1,500 features

- **Feature selection**
  - supervised
  - unsupervised
  - Selection
  - 10-20 features per fault type

- **Dimension reduction & classification**
  - LDA + kNN classifier
  - Artificial neural network
  - Support Vector Machines
  - 1-2 condition functions per component
  - classification

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Fully automatable!
Experimental Setup and Faults

- **Hydraulic test bench**
  - Consists of working and cooling-filtration unit
  - Experimental fault simulation of components
  - Two test benches
    1. for characterization of component faults
    2. for long-term and transferability analysis

**Experimental fault simulation of components**

**Experimental Setup and Faults**

<table>
<thead>
<tr>
<th>Comp.</th>
<th>Condition</th>
<th>Control parameter</th>
<th>Possible Range</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cooler C1</strong></td>
<td>Cooling power decrease</td>
<td>Fan duty cycle of C1</td>
<td>0…100 % of nominal current.</td>
</tr>
<tr>
<td><strong>Valve V10</strong></td>
<td>Switching charact. degradation</td>
<td>Control current of V10</td>
<td>0…100 % of nominal current.</td>
</tr>
<tr>
<td><strong>Pump MP1</strong></td>
<td>Internal leakage</td>
<td>Switchable bypass orifices (V9)</td>
<td>3 x 0.2 mm, 3 x 0.25 mm</td>
</tr>
<tr>
<td><strong>Acc. (A1-A4)</strong></td>
<td>Gas leakage</td>
<td>Accumulators A1-A4 with different pre-charge pressures</td>
<td>90, 100, 110, 115 bar</td>
</tr>
</tbody>
</table>

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**Hydraulic system I schematic** with PS pressure, FS flow, TS temperature, VS vibration, and EPS electric power sensors.
Fault Characterization Measurement

- Configuration of complex nested fault measurements
- Combination of all fault types and severity grades to involve interferences
- During measurement: test bench performs constant working cycle

Automated fault characterization measurement with duration of 36 hours

Constant working cycle, duration 60 sec, measured by PSI
Sensors and Data Acquisition

- Working cycle and data acquisition controlled by PLC
  - Sensor data synchronized with process
  - Sampling rate of each sensor type dependent on underlying physical quantity
  - Measurements of 17 process sensors (14 physical and 3 virtual sensors) and fault set points stored by DAQ-PC in CSV format
Feature Extraction Time Domain

- Computing feature values of each sensor and cycle interval
- Features used
  - Signal shape (slope, min, max, position of max, …)
  - Statistical (median, variance, skewness, …)

Iterating the sensors

Features used

Dividing cycle-wise data to sections

Calculating feature values

Pressure limitation
Valve operation
Load characteristics, static und transient sections

Feature Pool with ~ 1500 features
2-D LDA space shows the fault progression of components
DF1 allows the quantification of fault severity grade
Successful evaluation of statistical model by projection of fault grades not contained in training (→ interpolation)
Transferability of Statistical Model

- Training data with fault information collected with system I (~ 1 day)
- Subsequent feature extraction, selection and training of LDA
- Projection of long-term data (1 month) of system II with offset calibration

→ Learned statistical model transferable between systems with small adjustments
→ Long-term stability
Classification rates of or near 100% for studied fault scenarios

Transfer of statistical model successful

Detection of typical sensor faults possible

Compensation of up to 5 defect sensors

Computing time for training of ~120 Mio. raw data points
(17 sensors, 6000 values per cycle, 1250 cycles) @ Intel Core i5 CPU, 8 GB RAM

- Feature extraction: ~ 5 mins
- Feature selection: 0.2 sec per fault
- LDA: 0.1 sec per fault
- Classification of new cycle: < 0.1 sec per fault

→ technically feasible
Semantics-Empowered Fault Detection and Diagnosis

Semantic Domain Model
Hybrid Fault Detection Online
Semantic Diagnosis
Performance
Domain ontology in OWL2:

- Domain knowledge on concepts and relations
  - Machine components, sensors
  - Faults, symptoms, conditions
- Instances and sensor data (facts)

Based on HYDAC expert knowledge, ISO 2041, 13372, 17359:2011, W3C Semantic Sensor Ontology

Belief Network:

- Probabilistic knowledge on causal relations

Symptoms $S$ with $P(S|F)$
E.g. Pressure Level After Load

<table>
<thead>
<tr>
<th>Fault State Of Internal</th>
<th>No</th>
<th>Onset</th>
<th>Severe</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>0.0375078</td>
<td>0.0106759</td>
<td>0.1387599</td>
</tr>
<tr>
<td>Low</td>
<td>0.92470427</td>
<td>0.95025457</td>
<td>0.02212257</td>
</tr>
<tr>
<td>normal</td>
<td>0.0375078</td>
<td>0.0390775</td>
<td>0.0390775</td>
</tr>
</tbody>
</table>

Faults $F$ with $P(F|C)$
E.g. Pump Leakage

<table>
<thead>
<tr>
<th>Condition Of Pump</th>
<th>OK</th>
<th>Poor</th>
<th>Defective</th>
<th>Failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>0.5</td>
<td>0.5</td>
<td>0.1</td>
<td>1.0</td>
</tr>
<tr>
<td>Onset</td>
<td>0.05</td>
<td>1.0</td>
<td>0.6</td>
<td>0.0</td>
</tr>
<tr>
<td>Severe</td>
<td>0.05</td>
<td>0.6</td>
<td>0.6</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Conditions $C$ with $P(C|EF)$
E.g. Pump Condition

External Factors with $P(EF)$
E.g. PLC Signal, Operational Pump State

→ Automated logic-based and probabilistic reasoning for fault detection and diagnosis
Hybrid Fault Detection Online (1)

Multi-variate sensor data stream

Feature data stream bucket

[TS = “22.10.2014T22:10:23”; ct = (Kurtosis, 19.7, 29-30); vp = (Median, 9.3, 10-19); v = (Median, 4.0, 9-10); …]

- Semantic feature data annotation
  - (o2 type StatisticalFeature)
  - (o2 isStatisticalFeatureOf work_valve_pres)
  - (o2 hasFunction median)
  - (o2 hasValue “9.3”^^xsd:float)
  - (o2 hasWorkingCycleInterval static_working_cycle_1)
  - (o2 hasLevel “Low”)
  - (o2 hasTimeStamp “22.10.2014T22:10:23”^^xsd:dateTime)

- Logical inference of all implicit facts
  - (o2 type Symptom), (o2 type Static_Pressure_After_Load), (o2 hasState “low”), ...

Symptom queries:

REGISTER Query PALSWCI
SELECT ?f ?l
FROM STREAM <http://.../stream>
RANGE 1min STEP 1min
WHERE { ?f type Static_Pressure_After_Load.
   ?f hasState ?l. }

Retrieval of inferred actual symptoms

e.g. Static pressure (of valve) after load is low
Hybrid Fault Detection Online (2)

- Probabilistic inference of most likely fault states and conditions

**Symptoms:** (Static_Pressure_After_Load hasState “low”)  
**Ext. Factors:** (Operational_Pump_State hasState “active”)  

Statistical fault classification:

\[ P(\text{Pump}_\text{Leakage} = \text{Onset} \mid \text{SPAL} = \text{low}, \text{OPS} = \text{active}) = 0.7 \]
\[ P(\text{Pump}_\text{Leakage} = \text{Severe} \mid \text{SPAL} = \text{low}, \text{OPS} = \text{active}) = 0.2 \]

\[ \rightarrow \text{Semantic validation and explanation of statistical fault classification} \]
GUI: Detection and Diagnosis Online

Semantic Diagnosis
Inferred symptoms S with P(S|F) > 0.5
Semantic Diagnosis: Overview

iCM-Hydraulic system

- **Answers given diagnosis queries**

  with **query-specific combination of semantic reasoning tools**

  **Online:** (in parallel, over stream data)
  1. *Most likely explanation of detected component condition?* [C-SPARQL, GeNiLe]
  2. *Which other components are affected by detected fault(s)?* [STAR]
  3. *Semantic relations between these faults in the hydraulic circuit?* [C-SPARQL, STAR, Hermit, GeNiLe]

  **Offline:** (batch, over central store with historic data)
  4.- 6. Answer 1. – 3. over historic data [SPARQL, STAR, Hermit, GeNiLe]
  7. *Progression of component’s conditions and faults with probabilities?* [SPARQL]
  8. *Frequency of pump’s fault occurrence w.r.t. high fluid temperature level?* [SPARQL]

- **Generates human-understandable diagnosis results**

  with **query-specific semantic explanation templates**
Example: Semantic Diagnosis Online

Situation 1: Faults of pump, gas accumulator, pressure control valve.

Semantic relations with other component faults detected at same time?

* Pump pump1234 with internal pump leakage ipl123 is located before faulty component accumulator accu8774 with gas leakage agi456, detected at time 12.03.2015 23:00:09. Therefore, detected internal pump leakage might have caused detection of accumulator gas leakage.

* Pump pump1234 with internal pump leakage ipl123 is located before faulty component relief valve valve7645 with switching operation degradation sod789, detected at time 12.03.2015 23:00:09. Therefore, detected internal pump leakage might have caused detection of valve switching operation degradation.

Other components affected by detected component fault?

Displays other components monitored by sensors monitoring faulty component along with probable condition of components given the fault.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Monitored Component</th>
<th>Component Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>PressureSensor3</td>
<td>valve7645</td>
<td>OK(0.7)</td>
</tr>
<tr>
<td></td>
<td>accu8774</td>
<td>Poor(0.9)</td>
</tr>
<tr>
<td>PowerSensor1</td>
<td>valve7645</td>
<td>OK(0.7)</td>
</tr>
<tr>
<td></td>
<td>accu8774</td>
<td>Poor(0.9)</td>
</tr>
<tr>
<td>FlowSensor1</td>
<td>valve7645</td>
<td>OK(0.7)</td>
</tr>
<tr>
<td></td>
<td>accu8774</td>
<td>Poor(0.9)</td>
</tr>
</tbody>
</table>
Example: Semantic Reasoning

- What is the most likely condition of other components that are affected by the detected pump leakage, and which sensors are involved?

Part of Ontology:

- For each shortest path between machine components \( x \) and pump leakage instance \( y \) find symptoms \( s_1 \) of \( y \), \( s_2 \) of \( x \) with same monitored property \( p \).
- Retrieve sensor instances of Sensor \( \sqcap \exists \) observes. \( (P \sqcap \exists \) monitorsSymptoms\( (S_1 \sqcap S_2)) \).
- Compute most likely condition \( c \) of \( x \): \( \max_{x=c} \Pr(x=c|Y=s) \)
Example: Semantic Diagnosis Offline

- Progression of detected component’s fault states with probabilities?

- Frequency of pump leakage occurrence w.r.t. high fluid temperature level in the hydraulic aggregate?

- F.e. fault type occurrence in the past (interval) return average contamination values with change of fault grades
Performance of Semantic Diagnosis

- **Setting**
  - Hardware: i7@3.40 GHz; 16GB RAM, JDK 1.7; 14 GB MaxJVM-HeapSpace
  - Historic data:
    - Stream: 660 RDF triples/min
  - Recording Days
    | Recording Days | RDF-encoding | Materialization |
    |----------------|--------------|-----------------|
    | 1 [1440 working cycles] | 1,067,453 triples | 7,685,661 triples |
    | 2 [2880 working cycles] | 2,134,906 triples | 15,157,832 triples |

- **Fast average query response time**
  - *Online*: < 1 min
  - *Offline*: ~ 1 min

- Semantic annotation: 0.3 sec
- Semantic explanation: 1 sec
- Historic data loading: 15/35 min

- **High precision**: MAP = 1, Customer eval
  
  [8 test queries, rnd samples of test data for 1,250 working cycles with simulated grades of 4 component faults]
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Publications

- N. Helwig, S. Klein, A. Schütze: Identification and Quantification of Hydraulic System Faults based on Multivariate Statistics using Spectral Vibration Features; EUROSENSORS 2015, Freiburg, Germany, September 6 to 9, 2015; Procedia Engineering, doi: [10.1016/j.proeng.2015.08.835](https://doi.org/10.1016/j.proeng.2015.08.835)
- M. Klusch, A. Meshram, P. Kapahnke, A. Schuetze: ICM-Wind: Semantics-Empowered Fluid Condition Monitoring of Wind Turbines; Proc. 29th ACM Symposium on Applied Computing (SAC); Korea; ACM Press. available online
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