Predictive Maintenance using MATLAB: Pattern Matching for Time Series Data

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Focus:
• Digital Transformation
• Big Data
• IIoT

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We provide
• Algorithms
• Signal Processing
• Measurement Systems Developing
Optical System Design
Outline

1. Project introduction
2. Task description
3. Solution/Algorithm
4. Summary
POWERMTRAIN

Five modules form the core of our cars
The Powertrain production network is set up globally with lead plant in Germany.

**Europe**
- Hamburg
- Berlin
- Kamenz (ACCUmotive)
- Koelleda (MDC Power)
- Arnstadt (MDC Technology)
- Jawor/Poland
- Most/ Czech Republic
- Maribor/Slovenia
- Sebes and Cugir/Romania (Star Transmission)

**USA**
- Decherd (Cooperation with Renault/Nissan)

**China**
- Beijing (Joint Venture with BAIC Motor)

**Legend**
- ○ 100% Daimler
- ● Majority Holding
- ● Joint Venture
- ○ Cooperation

Predictive Maintenance using MATLAB: Pattern Matching for Time Series Data
Motivation for Anomaly Detection in the Projekt „iLL“

The goal is to detect anomalies in data

PLC-Data today:

Automatic Notification of the Deviation:

Source: www.autem.de
Data properties in the context of Big Data

The 3 basic V's of Big Data:

- **Velocity**: Speed with which data is generated and analyzed
- **Volume**: Amount of data that traditionally can not be analyzed
- **Variety**: Data diversity refers to unstructured data without a recognizable context

The 2 additional V's:

- **Validity**: Ensuring data quality
- **Value**: measurable benefits from the data
Benefits of „Intelligent Level-Learning“

Bearings damaged

- Normal cycle
  - Cycletime ✓
  - power ✓
  - Position ✓

- Different cycle
  - Cycletime ×
  - power ×
  - Position ✓

- Error cycle
  - Cycletime ×
  - power ×
  - Position ×

- Repair

Ensuring lean production by controlling quality, cost and time

Create maintenance order for unplanned breakdown

Procurement of spare parts; Downtime in production times

Active power engine axis 1
Position axis 1

Predictive Maintenance using MATLAB: Pattern Matching for Time Series Data
Challenges

• About 700 parameters are continuously monitored in every production cycle yielding 700 individual time-series of about 2500 samples each
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- Different parameters show very different and elaborate features
Challenges

- About 700 parameters are continuously monitored in every production cycle yielding 700 individual time-series of about 2500 samples each.

- Different parameters show very different and elaborate features.

Task: Analyse these 700 time-series and find specific kinds of deviations.
Requirements for algorithm

![Graph showing time deviation with production parameter D over time. The graph compares Cycle 1 and Cycle 2.]

- **Time, s**
- **Production parameter D**
- **Cycle 1**
- **Cycle 2**
Requirements for algorithm

Time deviation

Pattern deviation

Production parameter D

Production parameter E

Time, s

Production parameter E

Time, s

Cycle i

Cycle j

Cycle i

Cycle j
Requirements for algorithm

Time deviation **might not be critical**

Pattern deviation **is critical**
Requirements for algorithm

What the algorithm should do

- Time series analysis
- Find deviations from normal cycle and
- Distinguishing between time and pattern deviation

What is *normal*?
Delays in production cycles

- Length of time-series varies from cycle to cycle even for normal production
Delays in production cycles

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Delays in production cycles

- Length of time-series varies from cycle to cycle even for normal production

Normal cycles can be matched to one another through shifting in time axis!

![Graph showing cycle lengths over one day](image)

![Graph showing production parameter F](image)

Cycles from one day

Different delays

Perfect match after shift in time axis
Algorithm principle

normal cycle

\[\text{normal cycle graph}\]

test cycle

\[\text{test cycle graph}\]
Algorithm principle

- Cycle can be described as sequence of features f1, f2, f3
- Each cycle can show some delays in time t1, t2
Algorithm principle

• Cycle can be described as sequence of features f1, f2, f3
• Each cycle can show some delays in time t1, t2
• Automatic feature detection f1, f2, f3
Algorithm principle

- Cycle can be described as sequence of features $f_1$, $f_2$, $f_3$
- Each cycle can show some delays in time $t_1$, $t_2$
- Automatic feature detection $f_1$, $f_2$, $f_3$
- Pattern matching through shift of feature along time axis ($\Delta t_2$, $\Delta t_2$, $\Delta t_3$): least square fit ($t_{\text{shift}}$ to minimize the Sum of Residual Squares of two signals)
Algorithm principle

- Pattern matching through shift of feature along time axis ($\Delta t_2$, $\Delta t_2$, $\Delta t_3$): minimization of SRS
Algorithm principle

- Pattern matching through shift of feature along time axis ($\Delta t_1$, $\Delta t_2$, $\Delta t_3$): minimization of SRS
- Description of a cycle as feature sequence
- For each feature time and pattern deviation can be calculated
- Time and pattern deviation for each feature are used as characteristic numbers for test cycle

<table>
<thead>
<tr>
<th>$f_1$</th>
<th>$f_2$</th>
<th>$f_3$</th>
<th>Time deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Pattern deviation</td>
</tr>
</tbody>
</table>

Data reduction!
Automatic feature detection

Time series is split

- After a local extremum (maximum or minimum) or on a plateau
- After a given relative change

Data reduction of time series from 2500 datapoints to sequence of max. 60 features (typically 10)!
Algorithm implementation: machine learning approach in MATLAB

Reference cycles ->
- Build “reference signal“ for each feature
- Limits for time and pattern deviation

Test cycles ->
- Comparison of each feature in reference signal
- Is time and pattern deviation within the limits?
Create „reference signal“ for each production parameter

1. For all training cycles - matching to shortest cycle
2. Create „reference signal“ – mean over all matched reference cycles
Create „reference signal“ for each production parameter

1. For all training cycles - matching to shortest cycle
2. Create „reference signal“ – mean over all matched reference cycles
3. Possible pattern deviation - standard deviation over all matched reference cycles
Create „reference signal“ for each production parameter

1. Create „reference signal“ – mean over all matched reference cycles
2. Possible pattern deviation – standard deviation over all matched reference cycles, limits for SRS
3. Possible time deviation – maximal absolute shift from matched reference cycles
Testing: time and pattern deviation evaluation
Testing: time and pattern deviation evaluation

Is time and pattern deviation for this feature within the limits?

- Tolerance window ($\Delta t$, SRS)
- Easy to spot a critical deviation

Form: $10^3$ max SRS (norm.)

Time: max Shift (norm.)

Reference signal

Normal cycle

Error cycle
Testing: time and pattern deviation evaluation

Reference signal

Normal cycle

Error cycle

Production parameter $F$

Time, s

Testing
Algorithm: Summary

1. Quantitative and qualitative description of production failure
2. Independent of signal form -> universally applicable to other applications or machines
3. Signal description with characteristic numbers, which are easy to interpret
4. Data reduction with a factor 250 without significant loss of information!
5. Easy control of production: recognition of critical errors and non-critical delays online

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Example of the added value

**Example:** Change in code

Results:

- Transparency of the process
- Deviation for each Signal
- Reason of Cycletime increase found

➔ Time and Pattern deviation are recognized
Summary

Algorithm using pattern matching for time series developed and implemented for production data

Why MATLAB?
• easy algorithm implementation
• existing solution for data import
• very good support and broad use in universities

MATLAB Products used:
• Signal Processing Toolbox
• Statistics and Machine Learning Toolbox

Outlook:
• Parallel Computing Toolbox for performance improvement

Prototyp intelligent Level-Learning (iLL) has a new function for anomaly detection
• Troubleshooting in case of failure (maintenance), Parts Planning, Influences on the quality
  ➔ Optimization of repair time, spreaders amount, ...
Thank you for your attention!

**Mercedes-Benz**

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