Condition monitoring and fault diagnosis of vehicle components with on-board sensors

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Outline

- **Introduction**
  - Digital Operation Rail Systems
  - Machine learning on fault diagnosis of bogie components
- **Data-driven damper condition estimation**
- **Data processing and data-driven model generation**
- **Results**
- **Summary and outlook**

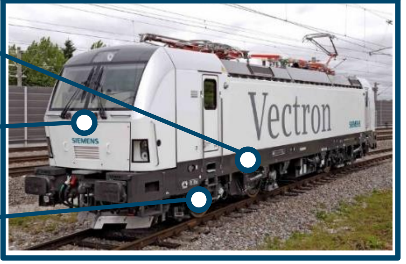
Digital Operation Rail Systems

virtual vehicle

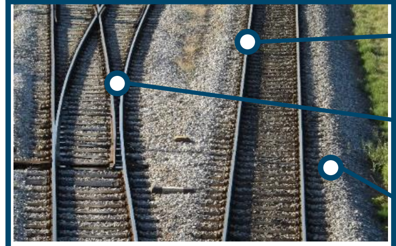
Decision Basis for Maintenance Systems

Rolling Stock

- Coupling Elements
- Dynamics
- Wheelsets



Railway Infrastructure



- Rail Geometry
- Switches
- Superstructure

Algorithm Development

- Model-based
- Data-driven

Health Monitoring Framework → **Current Status**

Prognosis System Framework → **Future Status**

Prescriptive Analysis Framework → **Impact of Measures**

Triple Hybrid Approach

Infrastructure (HW & SW)

- **Asset Management Tower at Industry / Operator**
- **System Lab at Virtual Vehicle**

Knowledge Generation

- Simulation
- Testing

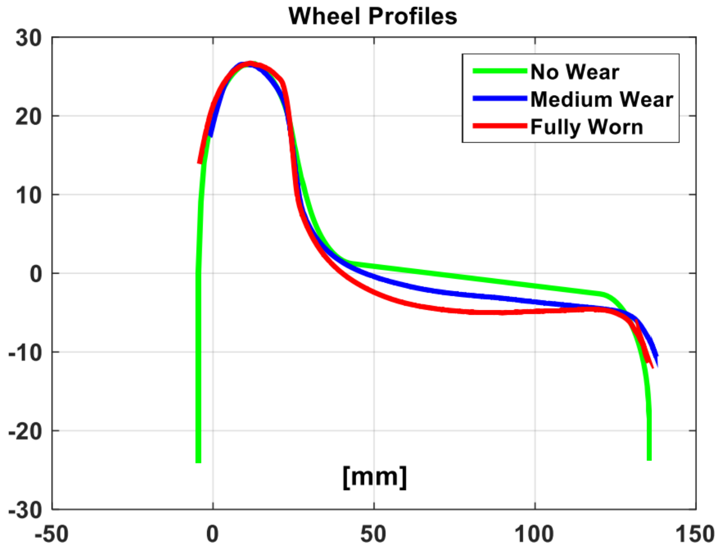
Data Acquisition

- On-board Monitoring
- Wayside Monitoring

Data-driven fault diagnosis – Use cases

Rail wheels profile

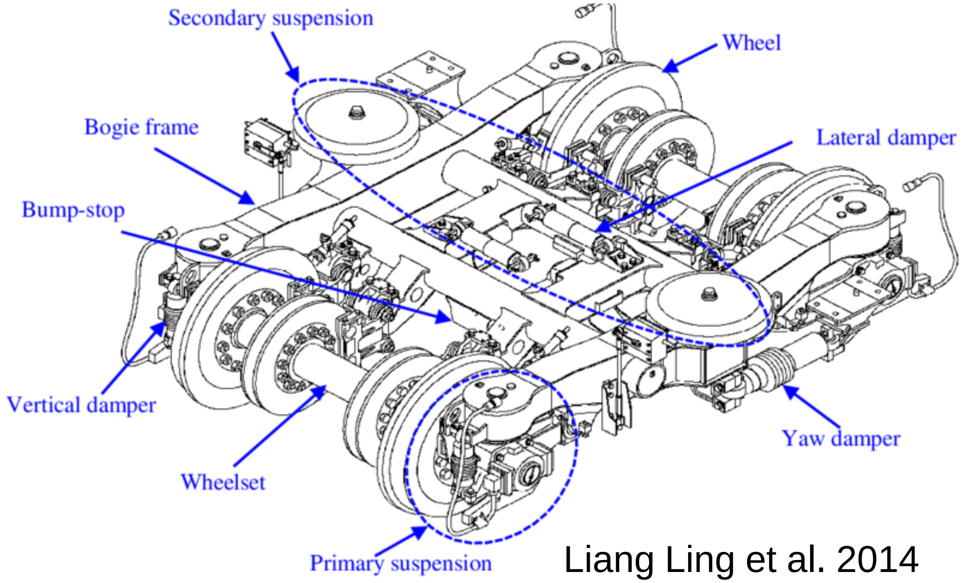
- Wheel wear detection and classification based on on-board inertial sensors
- Knowledge of 'significant' scenarios and operating conditions (distribution) is crucial to develop a successful classifier
- Simulation data



Shahidi et al. 2015

Bogie components

- Fault diagnosis of dampers with on-board acoustic sensors
- Test measured data



Liang Ling et al. 2014

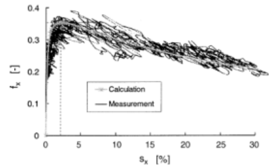
Data-driven fault diagnosis - Overview

Our way to approach the problem ...

Wheel profiles

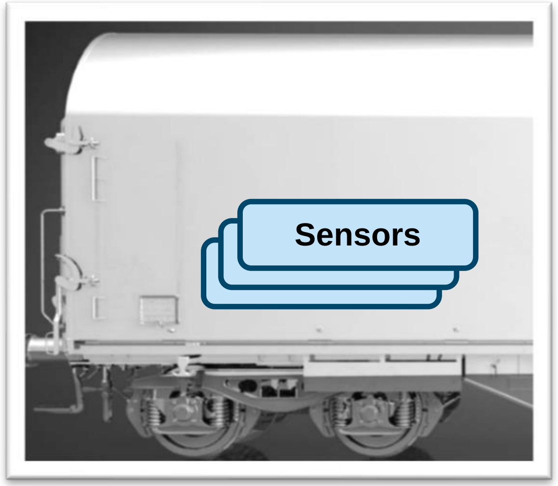
Loading

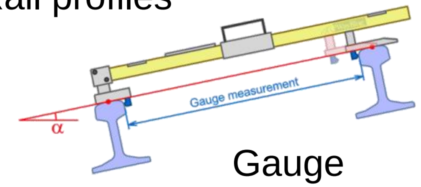
Speed



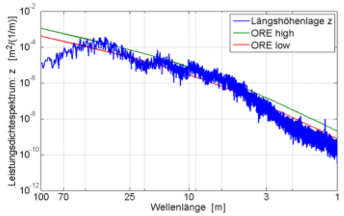
Friction

Rail profiles





Gauge



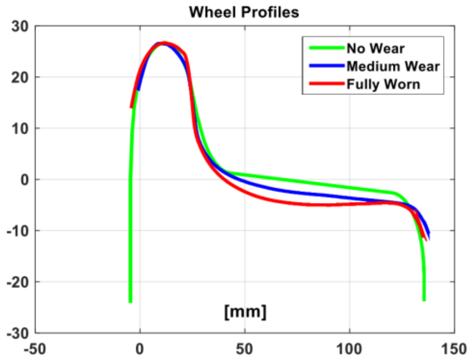
Track irregularities

Track layout

Machine Learning

Pre-processing → System knowledge (• Physical effects • Operating conditions) → Feature Extraction & Selection → Classification algorithm

Operating condition information → Classification algorithm



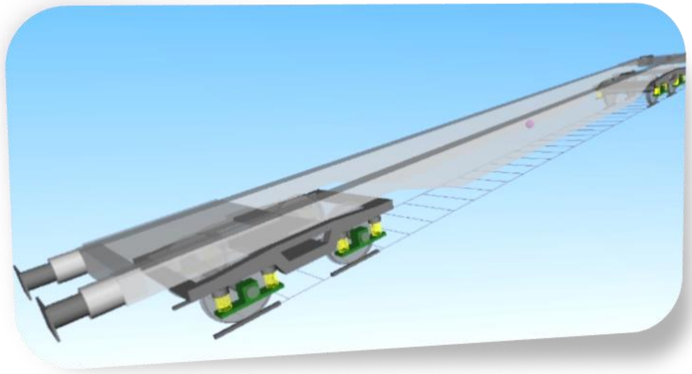
new worn

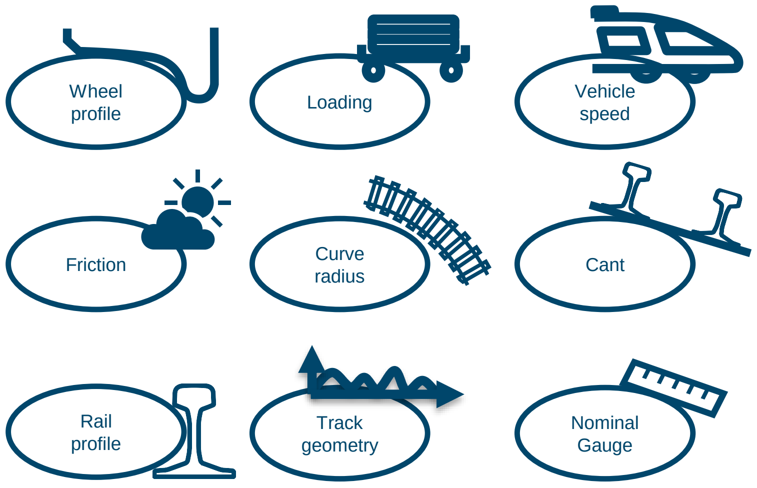
Wheel profiles

Data-driven fault diagnosis - Machine Learning

Machine Learning framework for this use-case

MBD simulations





Training and testing data

Changing operation condition ranges

Metrics
- Performance metrics
- → Accuracy

Features
- Feature extraction
- Feature selection

Algorithm
- Classifier selection
- Optimization algorithm

Performance
- Performance evaluation
- Classifier validation

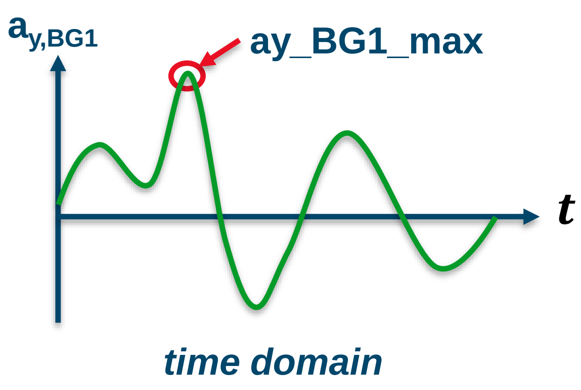
	Worn profile (positive)	New profile (negative)
Pred. pos. "Worn profile"	True positive (TP)	False positive (FP)
Pred. neg. "New profile"	False negative (FN)	True negative (TN)

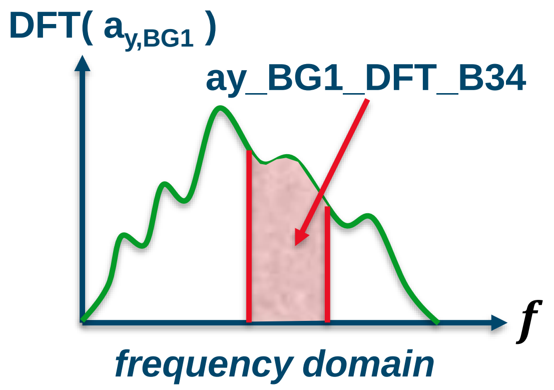
$$Accuracy = \frac{(TN + TP)}{(TN + TP) + (FP + FN)}$$

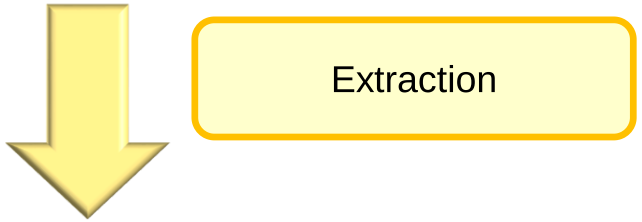
Machine Learning - Feature extraction & selection

Feature extraction from all sensor

- Time domain:
  - max, std, kurtosis, skewness, peak-to-peak, ...
- Frequency domain:
  - spectral peak, energy in frequency bins, ...
- Time-frequency domain:
  - Spectral kurtosis, STFT, EMD, WVD,…

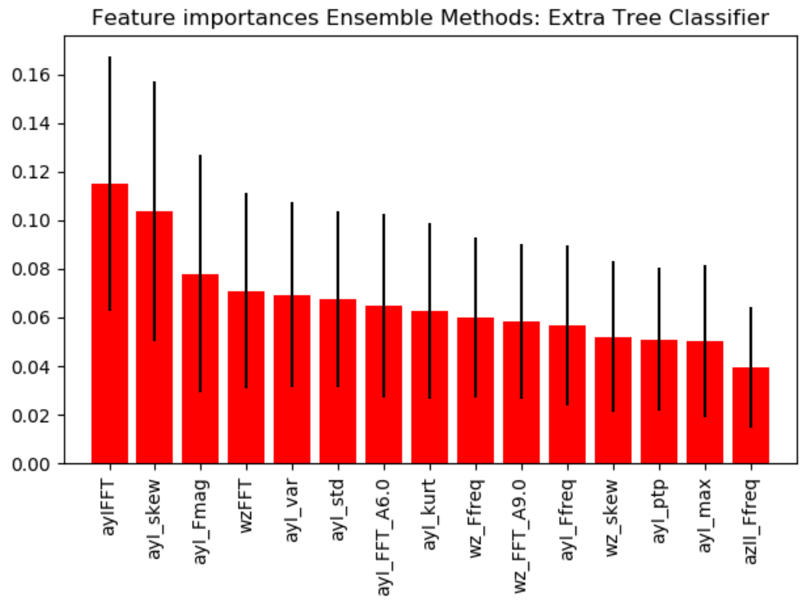


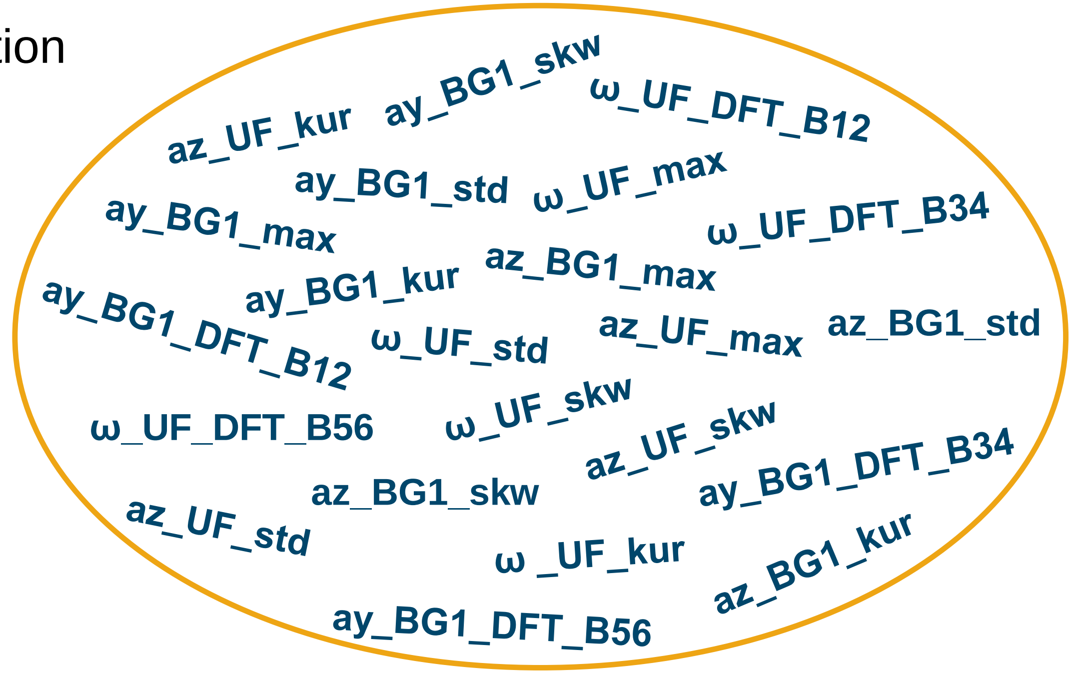




Feature selection

- Goal: Find a minimum number of features for a robust classification

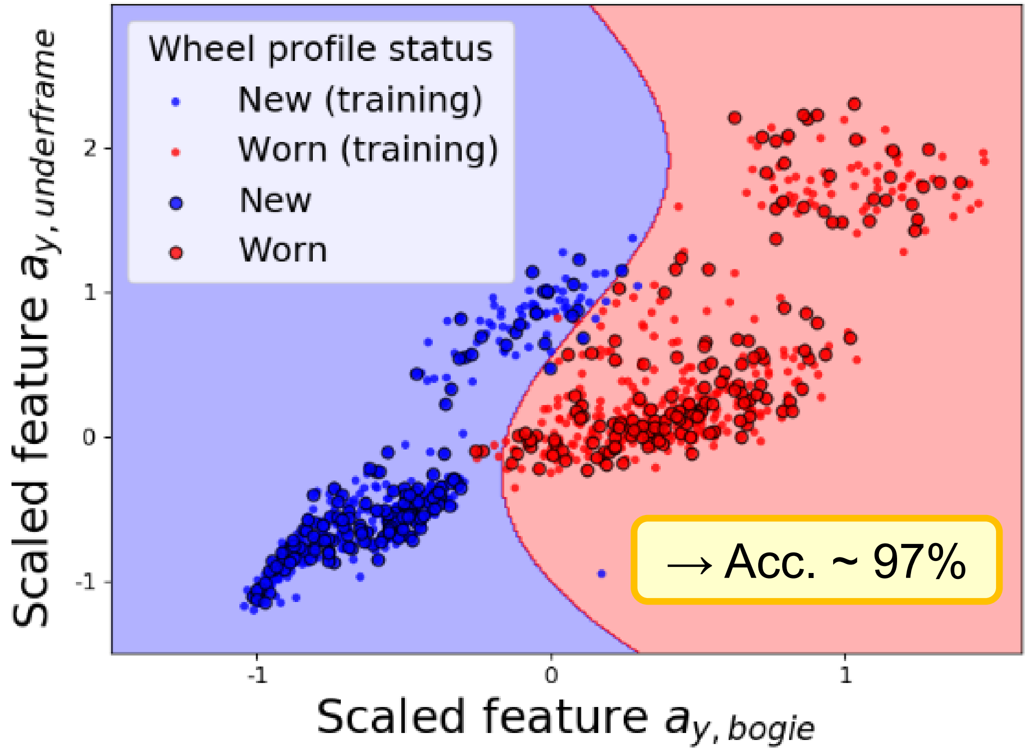




Monitoring railway wheels

Classification of worn and new profile

- Parameter study (running behaviour) based on **MBD simulations**
  - System parameter
  - Operating conditions
- Expected influence of different wheel-profile conditions
- High influence of 'other operating' conditions
- Separation seems easier in curved tracks
- 'Physics' explain the observations
- Machine Learning (ML) algorithms verify the hypothesis
  - two features from lateral acceleration of the bogie and carbody were enough to separate new from worn profile
  - results were used to develop wheel wear degradation models for predictive maintenance



⇒ Knowledge of operating conditions where higher lateral movement lead to higher axle box accelerations is essential for Machine Learning classification results!

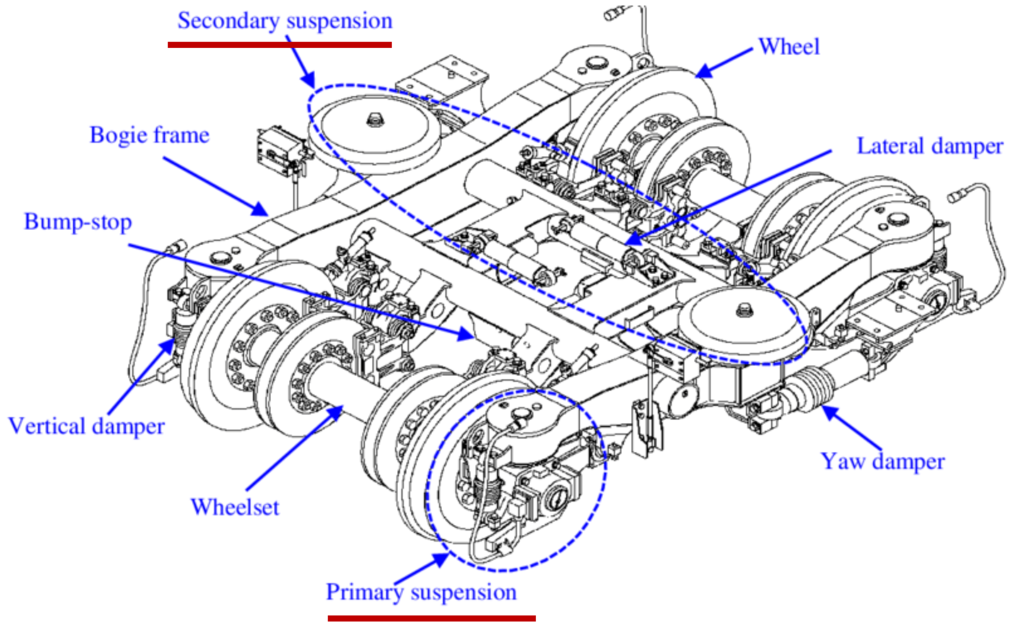
Monitoring bogie suspension dampers - Objectives

Main goal:

- Feasibility study for condition monitoring of bogie suspension dampers with on-board acoustic sensors

Secondary objectives:

- Find signal features that contain information from faulty behaviour
- Find features to classify a fault independently of fault location and train operating condition
- Find the best operation conditions to isolate each fault
- Validate and verify robustness of the methodology and explore its possibilities on fault diagnostics

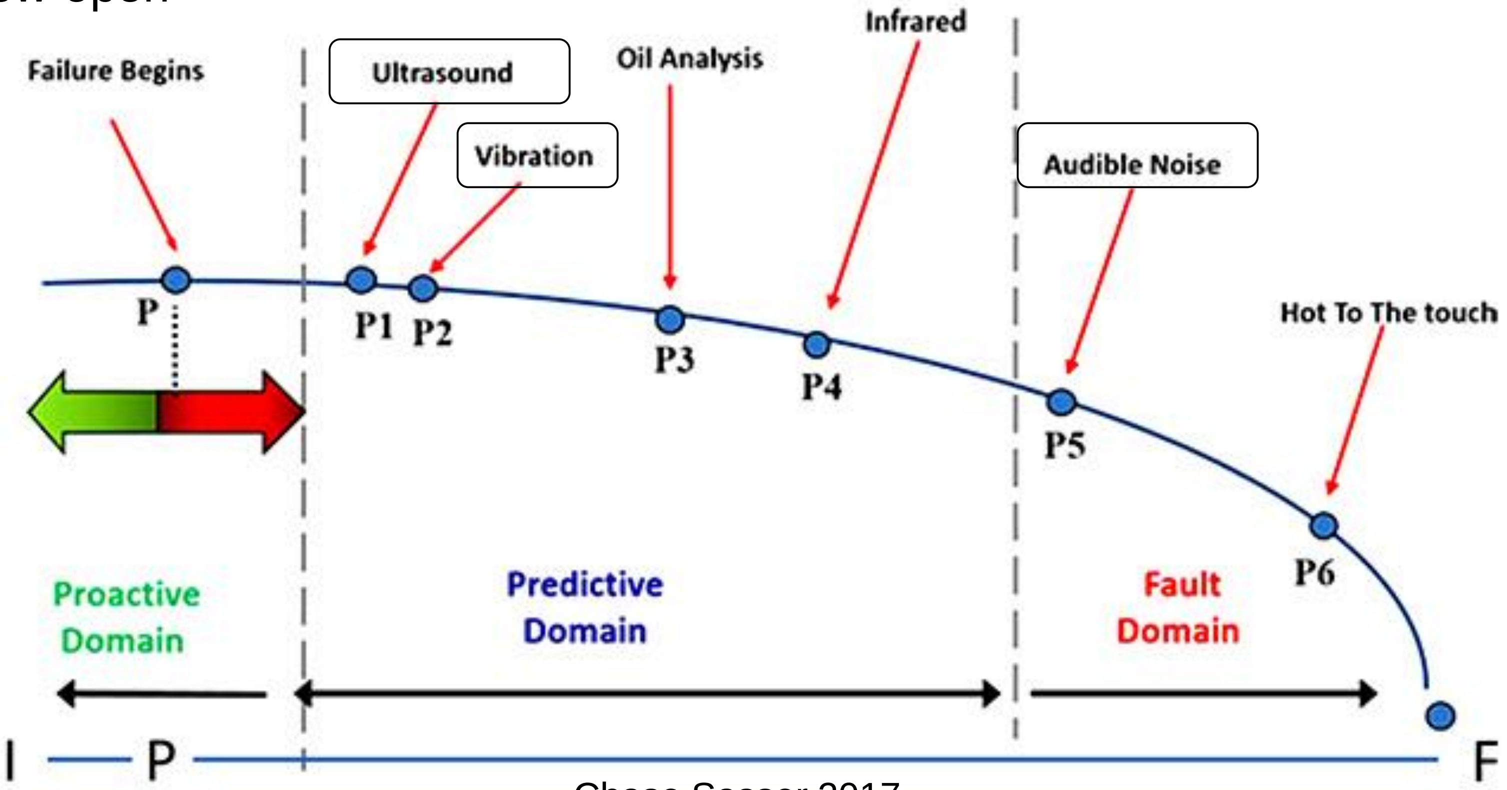


Monitoring bogie suspension dampers - Sensors

virtual vehicle

Acoustic vs inertial sensors in train CBM

- Structure components (beams, masses, dampers, springs, junctions) act as signal filters.
- Locating the sensors close to the components exposes it to higher fatigue loads
- Fault acoustic emissions (AE) can be detected before structural vibrations are detectable with inertial sensors → Potential failure (P) vs functional failure (F)
- “Like a stone” in a car tire, you don´t feel the acceleration difference when driving but you can ear it if you drive slow with the window open

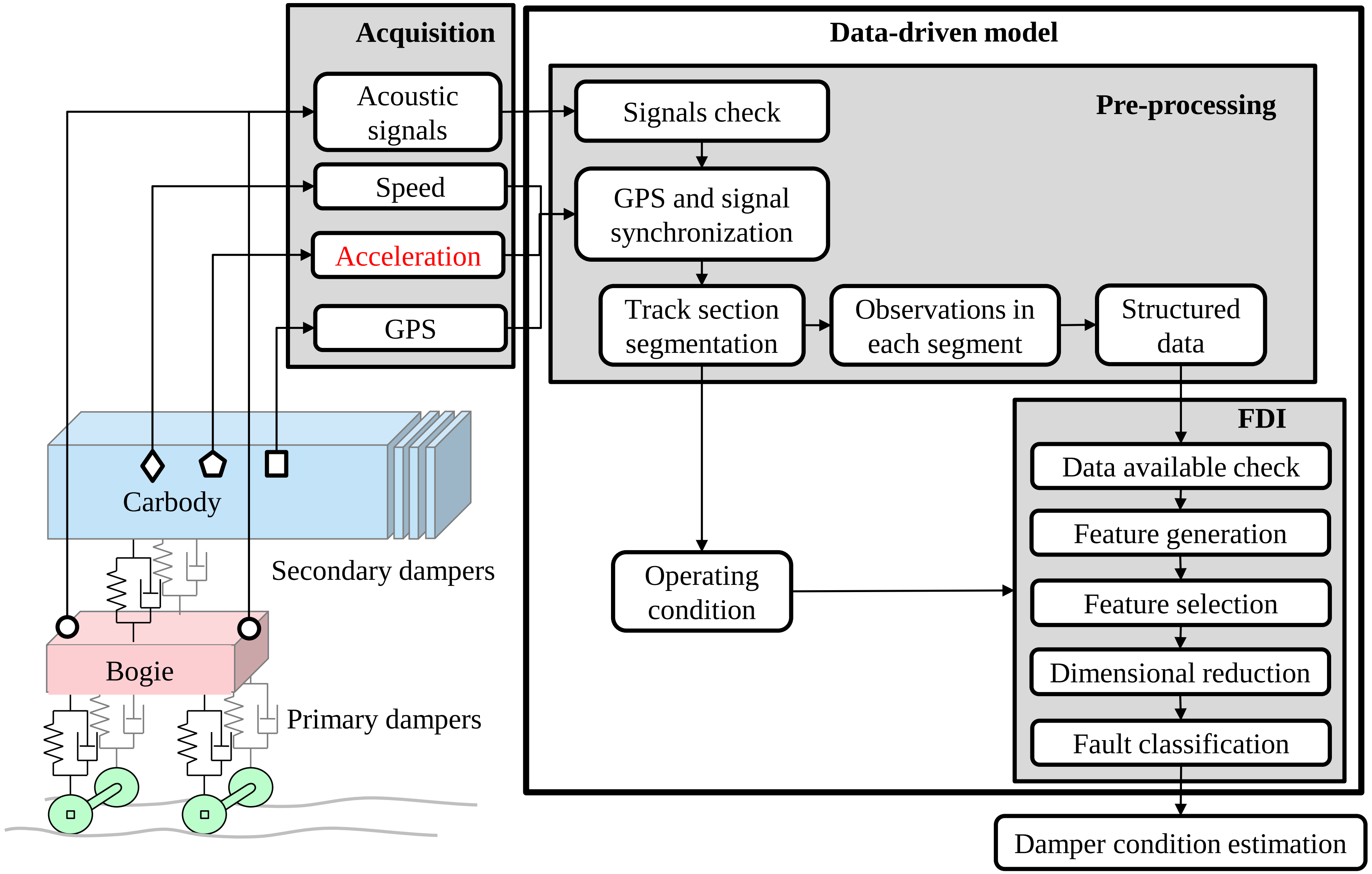


Chase Sasser 2017

Data-driven damper condition estimation - Methodology

Damper condition estimation:

- **Data acquisition**
- **Data preprocessing**
  - Data cleaning
  - Signals synchronization
  - Track segmentation
  - Observation samples into a data structure
- **Fault detection isolation (FDI)**
  - Data available check
  - Feature generation
  - Feature selection
  - Fault classification

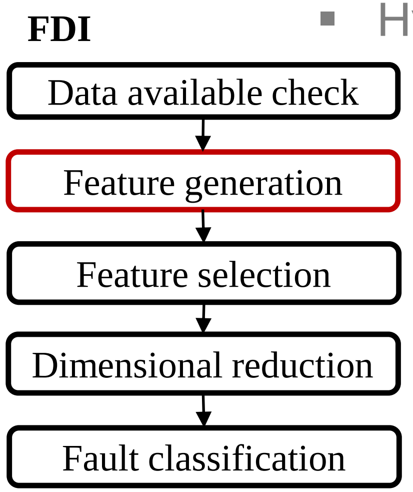


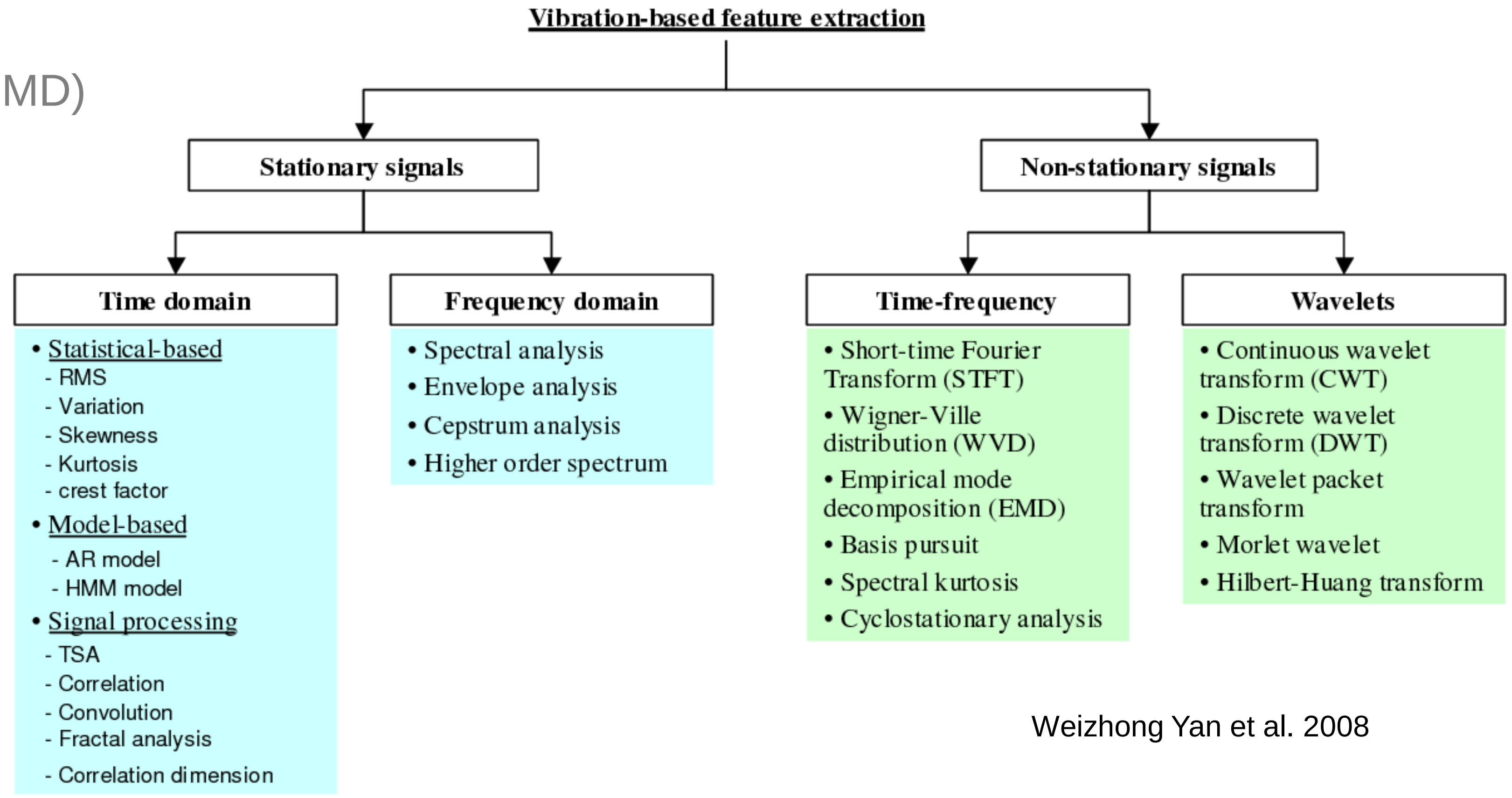
Data-driven models' generation – Feature generation methods

Feature generation from stationary and non-stationary vibration signals

- **Time domain features**: e.g. max, peak-peak, median, std, crest factor, skewness, kurtosis, crest factor
- **Frequency domain features**: e.g. FFT (magnitude and phase), PSD, spectral centroid, spectral spread, spectral bandwidth
- **Time-frequency domain features**
  - Short-time Fourier Transform (spectrogram), Mel Frequency Cepstral Coefficients (**MFCC**)
  - Winer-Ville distribution (WVD)
  - Empirical model decomposition (EMD)
- Hilbert–Huang transform
- Wavelets
  - Discrete wavelet transform (DWT)
- Hybrid approach:

  Features from model-based and data-driven



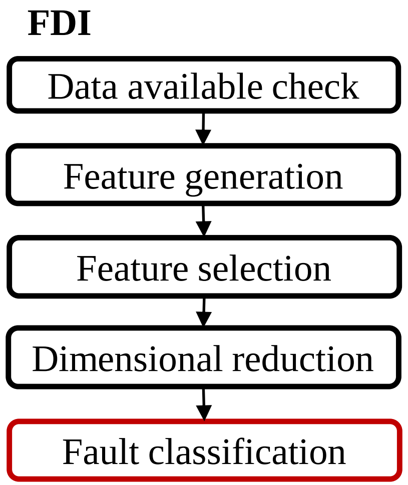


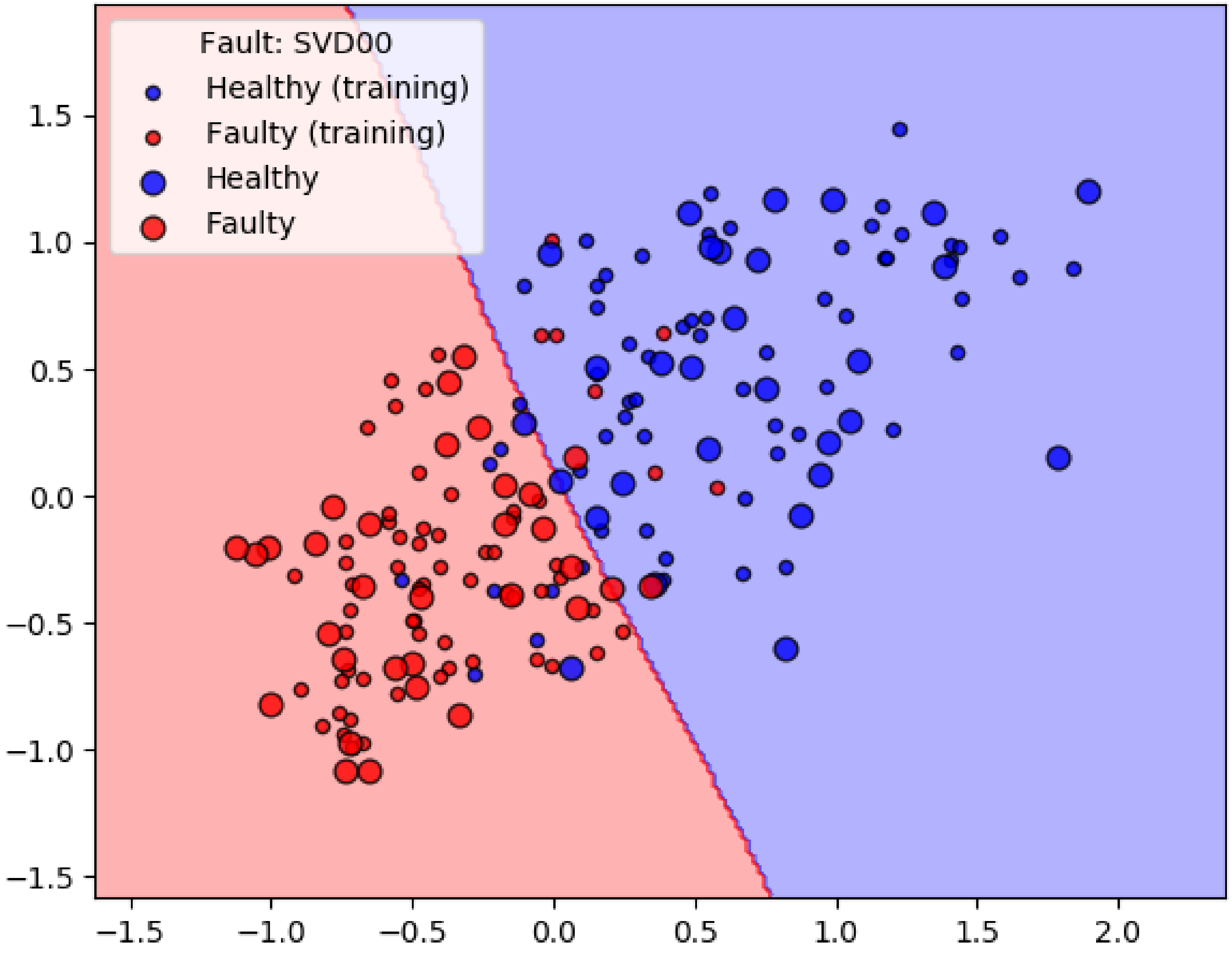
Weizhong Yan et al. 2008

Results – Faulty damper classification

Sensors on bogie side frame

- Classification performance is highly influenced by the level of excitation
- Features filtering aerodynamic noise increased classification performance considerably
- In straight track sections all faults were successfully classified using just 2 features
- Secondary vertical damper removed (SVD00) is easier to classify in straight and transition track sections





How could this methodology be applied on ships SHM?

Ship structural problems:

- Corrosion and fatigue cracking are the most pervasive types experienced in ship structures

Objective:

- Reduce welding and operation costs through predictive maintenance (dry-docking is expensive)

Methods:

- Acoustic Emissions method has been successfully used to inspect large offshore structural integrity
- **Data-driven approach:**
  - Training models with measured data from onboard sensors like: AE sensors, accelerometers, microphones, temperature, strain, humidity and gas sensors
  - Sensitivity analysis to find most important features to characterize structural health condition
  - Performing anomaly detection and fault diagnosis using machine learning methods
  - Prognostics fitting degradation models
- **Model-based and hybrid approaches:**
  - Generate vibroacoustic models to monitor welded joints with high stress and validate with measurements
  - Train data-driven models with results from vibroacoustic

Estimation of structural damages of ship hull

Analysis of qualitative and quantitative influence to the structural integrity

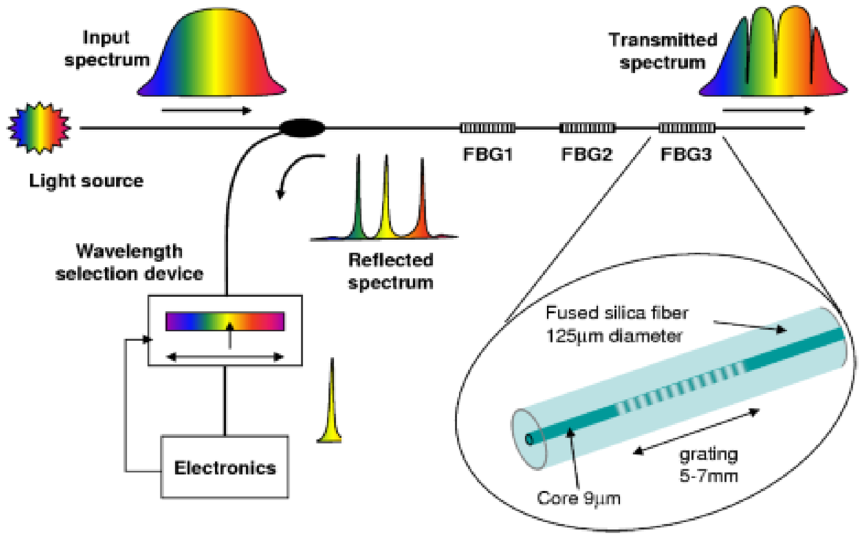
- External loads, material characters, component shape, surface condition, corrosion severity, existing cracks, static and dynamics stress load

Analysis of Non-Destructive Testing signal processing

- Pre-processing
- Feature generation / selection
- Pattern recognition / classification
- Prognostics

Damage monitoring

- Detection
- Localization
- Assessment
- Life prediction



LIGHT STRUCTURES SENSFIB

Table 5.3: Support Vector Machine classification results of KDE-based patterns and the associated damage mechanisms

	Class 1	Class 2	Class 3	Class 4
Detection rate [%]	85.24	79.72	94.69	86.81
AE event	C3	C4	C2	C1
Damage	Fiber breakage	Matrix cracking	Debonding.	Delamination

Baccar 2015

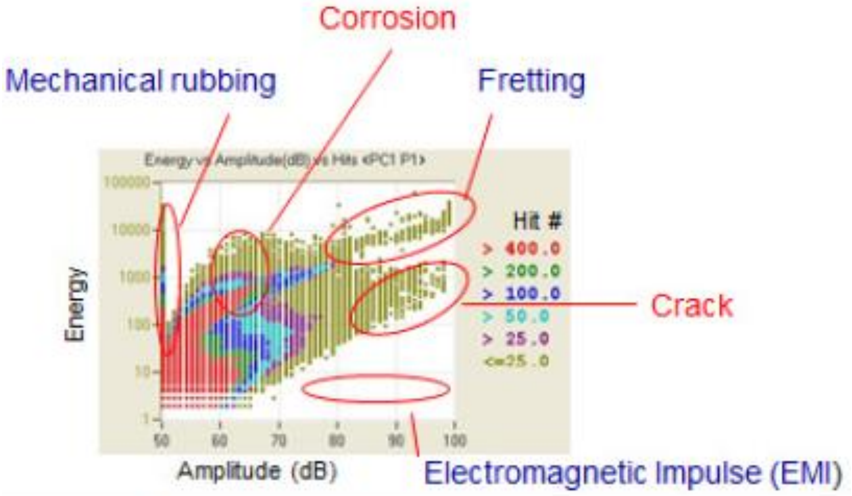


Figure 7: Correlation Plots for Pattern Recognition

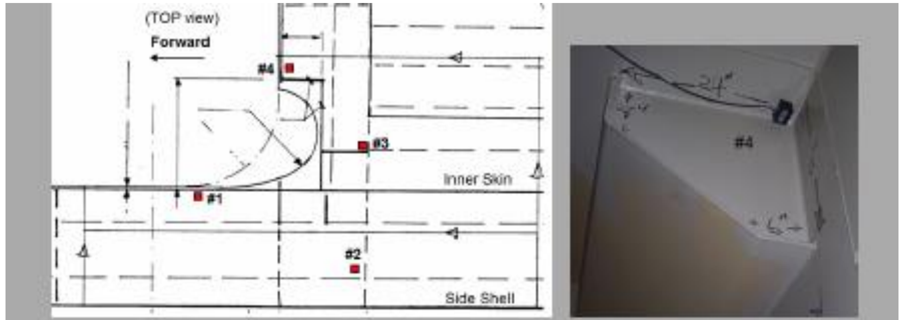


Figure 13: AE Sensor Locations at Hatch Corner Area (P1 Area)

AiKuo Lee et al. 2014

Summary & Outlook

Summary

- Digital Operation Rail System has successfully applied system knowledge and machine learning on:
  - Wheel wear prognostics
  - Suspension dampers fault diagnosis
- The feasibility study of monitoring bogie dampers with data-driven models using acoustic sensors has been validated with two measurement campaigns

Outlook

- Data combination from different sensors (accelerometers and microphones)
- Environment operating condition detection
- Component condition estimation through regression (supervised learning)
- Development of on-board prognosis algorithms for damper degradation predictions
- Unsupervised learning from monitored in-service trains

virtual vehicle

Enabling future vehicle technologies

Questions & Discussion

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FFG Promoting Innovation.
Das Land Steiermark
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TU Graz Graz University of Technology

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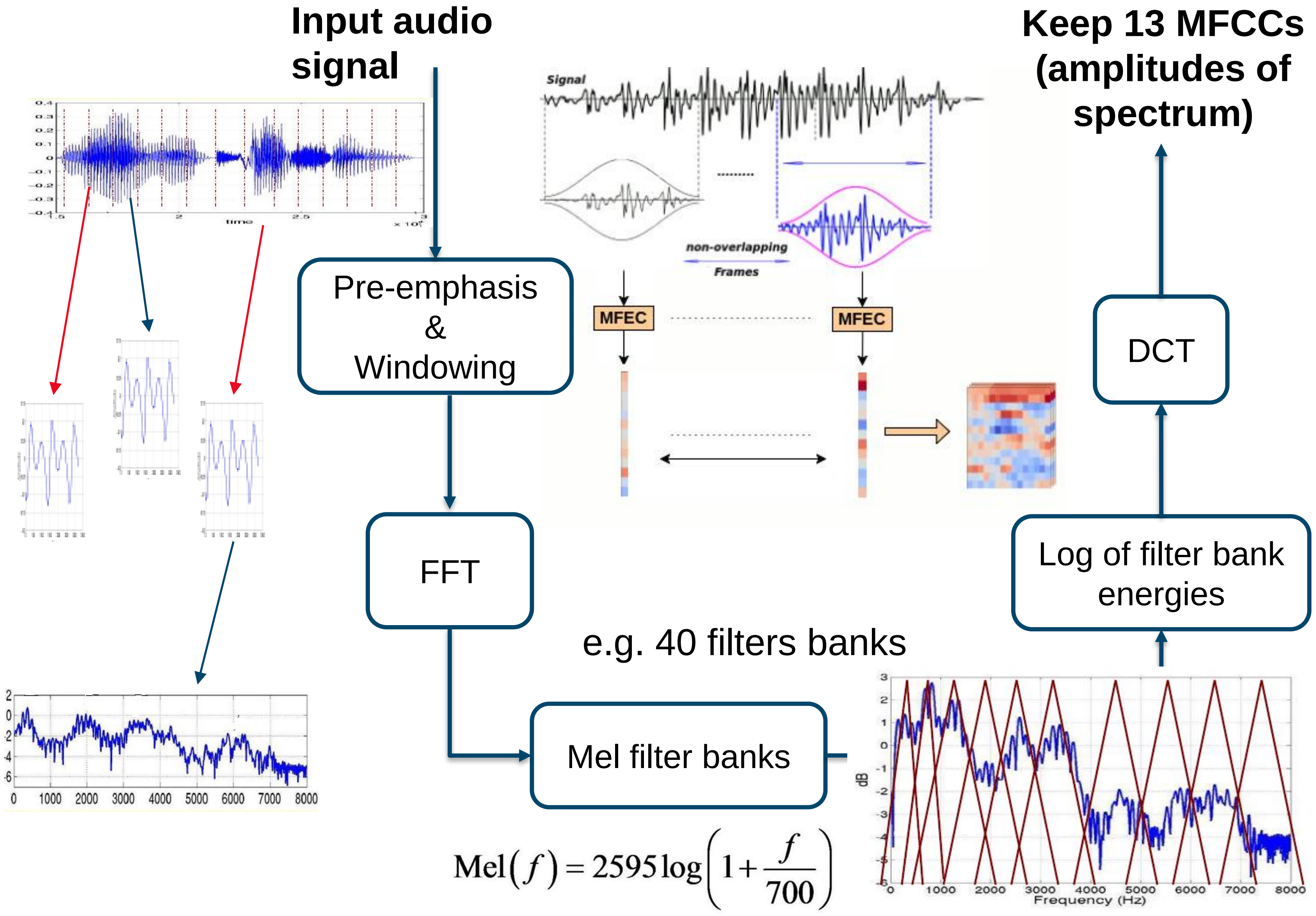
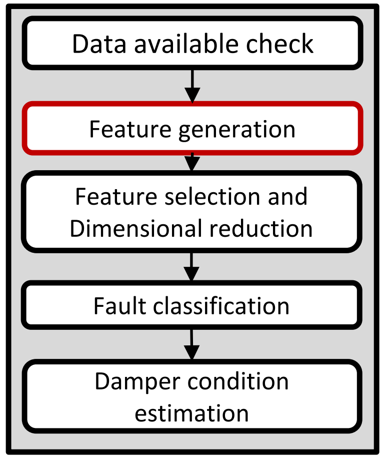
Mel Frequency Cepstral Coefficients (MFCC)

- Widely used in automatic speech recognition systems
- Keeps only relevant features, discards other sounds that carries Information like background noise, etc
- Triangle filter banks are spaced according to the mel frequency scale
- Inverse Discrete Cosine Transformation (DCT) is used to decorrelate the outputs and reduce dimensionality



$$\mathrm{Mel}(f) = 2595 \log\left(1 + \frac{f}{700}\right)$$

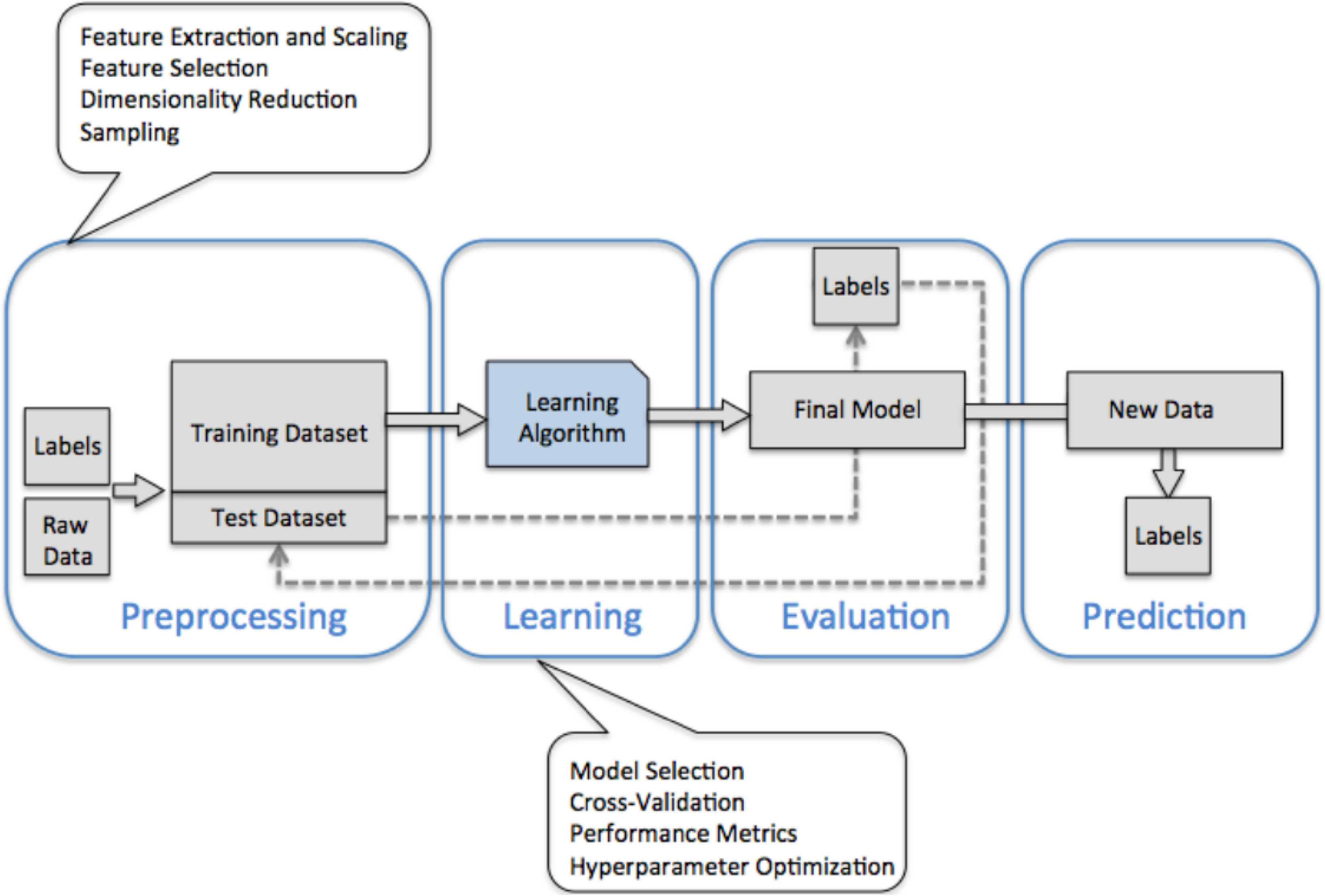
FDI



Supervised learning flow

Cross-validation

- K-fold training dataset israndomly split into *k* folds without replacement, where *k*−1 folds are used for the model training and one fold is used for testing. This procedure is repeated *k* times and performance estimates.
- Stratified k-fold cross-validation yield better bias and variance estimates, especially in cases of unequal class proportions



Sebastian Raschka 2015