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Recommendations for Data-Driven Degradation Estimation with Case Studies from Manufacturing and Dry-Bulk Shipping

Authors: N. Finke, M. Mohr, A. Lontke, M. Zünfle, S. Kounev, R. Möller

Alexander Lontke

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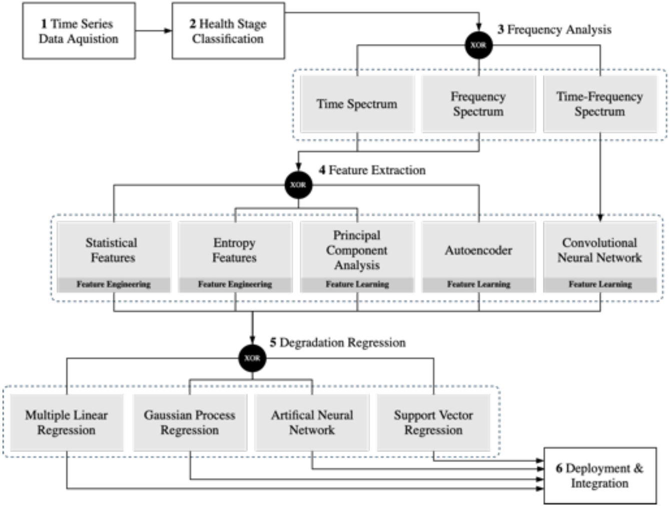
Introduction
Challenge

- **Predictive maintenance** reduces the risk of unwanted production downtimes
- Degradation models extrapolate future conditions from historical behaviour by regression
- Data typically in the form of time series which are incompatible with classical regression methods
- **Feature extraction** integral part of the process
- Existing approaches poses significant challenges: User does not know what to use in which combination

Introduction
Contribution

- **General approach** for composing existing process steps such as
  - health stage classification
  - frequency analysis
  - feature extraction or
  - regression models for the estimation of degradation
- Several experiments in **two comprehensive case studies**, one from manufacturing and one from dry-bulk shipping
- **Recommendations** for composing a data-driven degradation estimation process

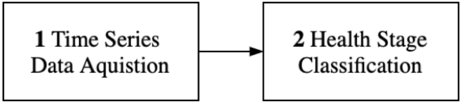
A Data-Driven Approach for Degradation Estimation



A Data-Driven Approach for Degradation Estimation

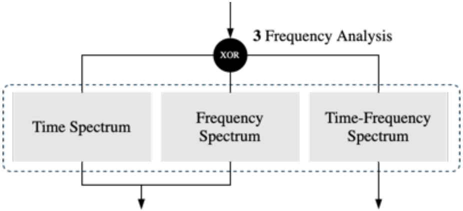
Health Stage Classification

- Optional step in our approach
- Healthy data outweighs degradation data in regular operation
  - Could impede prediction process or add bias
- Identifies first prediction time (FPT)
- Data that is classified as healthy is omitted from both training and prediction



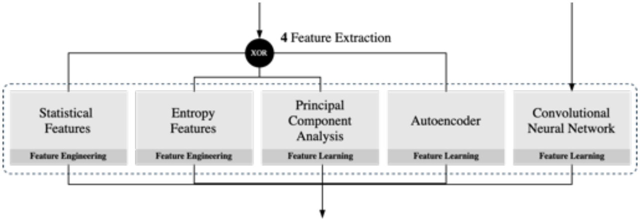
A Data-Driven Approach for Degradation Estimation
Frequency Analysis

- Analyse frequency range of a time series
- Again optional
- Time spectrum: raw time series
- Frequency spectrum: Fourier transformed time series
- Time-Frequency spectrum: short-time Fourier transform



A Data-Driven Approach for Degradation Estimation

Feature Extraction



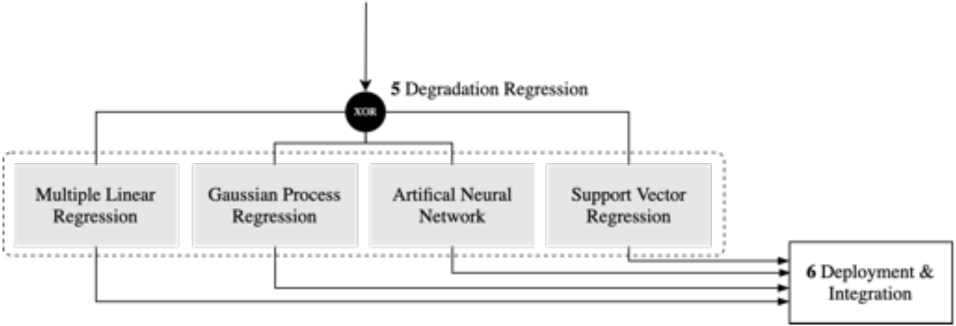
Feature Engineering

- Create new features by...
  - ...domain-specific knowledge
  - ...transforming data
- Applicable to both time and frequency spectrum

Feature Learning

- Solve mathematical optimisation problem to create new features
- Can reveal task-specific patterns not obvious to humans

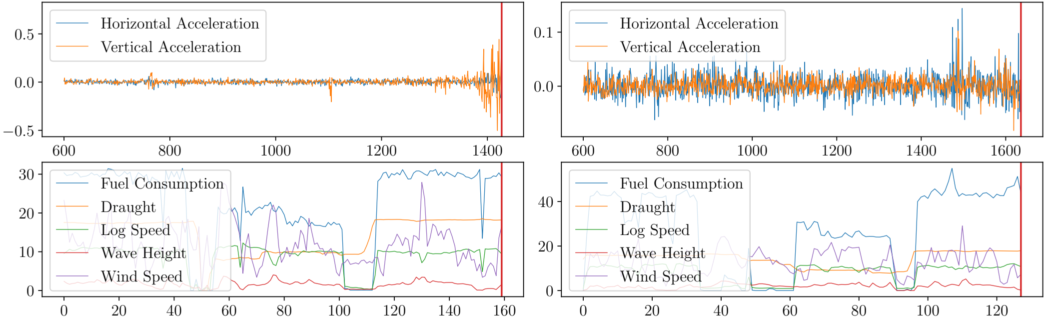
A Data-Driven Approach for Degradation Estimation
Degradation Regression



- Fit historical data
- Predict continuous variable (in this case remaining useful lifetime (RUL))
- Many different regression methods available

Case Studies

Bearing and Vessel Data



Case Studies
Experimental Settings

- 104 experiments in total
- $Z_{i,j}$ is an experiment, where $Z \in \{A, \ldots, M\}$
- $i \in \{\mathrm{true}, \mathrm{false}\}$ denotes if the health stage (HS) classifier is used
- $j \in \{$MLR, GPR, ANN, SVR$\}$ denotes the selected regression model
- Metrics used: root mean square error (RMSE) and Pearson correlation coefficient (PCC)
- Code available on GitHub

	Statistical Features	Entropy Features	PCA	Autoencoder	Statistical+ PCA	Statistical+ Autoencoder	CNN
Time Spectrum	A	B	C	D	E	F	–
Frequency Spectrum	G	H	I	J	K	L	–
Time-Frequency Spectrum	–	–	–	–	–	–	M

Figure: All combinations of frequency analysis and feature extraction steps used in the case studies.

Case Studies

Research Question 1: Health Stage Classification

Metric	MLR	GPR	ANN	SVR
RMSE Improvement	(59|100)%	(78|97)%	(64|92)%	(74|92)%
PCC Improvement	(41|59)%	(63|28)%	(34|41)%	(69|38)%

	Statistical Features	Entropy Features	PCA	Autoencoder	Statistical+ PCA	Statistical+ Autoencoder	CNN
Time Spectrum	A	B	C	D	E	F	–
Frequency Spectrum	G	H	I	J	K	L	–
Time-Frequency Spectrum	–	–	–	–	–	–	M

- Results are written using the notation (bearing | vessel)
- In general improvement is observed

Case Studies

Research Question 2: Time vs. Frequency Spectrum

Using FA	Statistical	Entropy	PCA	AE	Stat.+ PCA	Stat. + AE
RMSE Improvement	(42|21)%	(50|58)%	(47|8)%	(38|50)%	(52|50)%	(55|42)%

- Only the case of $B_{i,j}$ vs. $H_{i,j}$ shows improvement, regarding average RMSE and average PCC
- $D_{\text{true,GPR}}$ and $E_{\text{true,MLR}}$
  - Bearing data: increase in RMSE in 100% of the predictions
  - Vessel data: decrease in RMSE in 100% of the predictions

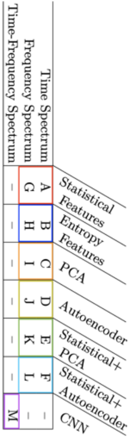
	Statistical Features	Entropy Features	PCA	Autoencoder	Statistical+ PCA	Statistical+ Autoencoder	CNN
Time Spectrum	A	B	C	D	E	F	–
Frequency Spectrum	G	H	I	J	K	L	–
Time-Frequency Spectrum	–	–	–	–	–	–	M

Case Studies

Research Question 3: Appropriate Feature Sets (bearing data)

Metric	Statistical	Entropy	PCA	AE	Stat.+ PCA	Stat.+ AE	CNN
Average RMSE	6.962	6.265	13.603	13.513	7.082	6.721	6.238

- Engineered features on average better than learned features
- Feature Learning on engineered features is more efficient
- Convolutional neural networks performs best, followed by entropy features

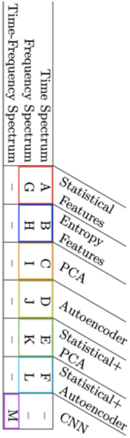


Case Studies

Research Question 3: Appropriate Feature Sets (vessel data)

Metric	Statistical	Entropy	PCA	AE	Stat.+ PCA	Stat.+ AE	CNN
Average RMSE	240	323	324	430	338	277	335

- Suggesting statistical features are particularly effective or autoencoder particularly ineffective
- In contrast to bearing data, no evident outliers, except for $\{B, D, J\}_{i,\text{GPR}}$, which is related to the regression model



Case Studies

Research Question 4: Regression method

Metric	MLR	GPR	ANN	SVR
Average RMSE	(22.677|295)	(87.091|459)	(9.578|267)	(8.041|272)
Average PCC	(0.13|0.01)	(0.05|0.07)	(0.28|0.01)	(0.21|0.03)

- Support vector regression and artificial neural network prove most beneficial

	Statistical Features	Entropy Features	PCA	Autoencoder	Statistical+ PCA	Statistical+ Autoencoder	CNN
Time Spectrum	A	B	C	D	E	F	–
Frequency Spectrum	G	H	I	J	K	L	–
Time-Frequency Spectrum	–	–	–	–	–	–	M

Conclusion
Open Challenges

- Numerous other methods for HS classification, frequency analysis, feature extraction and regression
- The application of regularisation
- Feature selection methods
- Corresponding hyperparameter tuning
- Optimisation of network architectures are left for future work
- Learning non-linear relationships, as by locally linear embeddings, isometric mappings or kernel principal component analysis (PCA)
- Combination of time and frequency spectrum features

Conclusion

Recommendations for Data-Driven Degradation Estimation

- **Health Stage classifier**:
  - Integrate a HS classifier within the degradation estimation process
  - In the vast majority of cases both RMSE and PCC are improved
  - There are other HS classifiers that may be more appropriate for your individual problem
- **Frequency analysis**:
  - We do not recommend predicting the degradation solely by features calculated on frequency spectra
  - This does not mean that such features cannot add value in combinations with others

Conclusion

Recommendations for Data-Driven Degradation Estimation

- **Feature set**:
  - While CNN and entropy features are most suited for bearing data, classical statistical features are for vessel data
  - The feature extraction method can be easily replaced in the process later
- **Regression model**:
  - We do not recommend MLR and GPR
  - ANN and SVR perform best, with ANN being able to better represent the functional relationship.
  - SVR is known for good generalisation ability, which is also shown here

Happy to answer questions!

Alexander Lontke

github.com/inovex/RCIS2021-degradation-estimation-bearing-vessels

alexander.lontke@inovex.de