Density based Anomaly Detection for Wind Turbine Condition Monitoring

Johannes Bernhard[1,4,*], Jonas Schmidt[2,4] and Mark Schutera[3,4]
[1]*Karlsruhe Institute of Technology, Institute for Information Processing Technologies, Germany*
[2]*University of Osnabrück, Institute of Cognitive Science, Germany*
[3]*Karlsruhe Institute of Technology, Institute for Automation and Applied Informatics, Germany*
[4]*ZF Friedrichshafen AG, Research and Development, Germany*

Keywords: Condition monitoring, Machine learning, Environmental engineering, Anomaly detection.

Abstract: Unsupervised and explainable approaches are critical in anomaly detection for mechanical systems. This work proposes a density-based k-nearest neighbor method to combine an unsupervised learning setup with the added value of explainability. The algorithm is applied to detect anomalies in vibration data from acceleration sensors or microphones. In a training phase, we transform healthy vibration data into mel-spectrograms and extract feature patches representing healthy turbines' vibration energy distribution. We determine anomaly scores by calculating a k-nearest neighbor similarity between operational feature patches and healthy feature patches. Hence, we use basic statistical methods with interpretable results, which contrasts with deep learning techniques. The evaluation paradigm is data from damaged and healthy wind turbines and a secondary machine audio data set. This work introduces and explores a novel sensor-level anomaly score. The model identified all damaged sequences as anomalies on the wind turbine sequences. Furthermore, the method achieved competitive results on the more complex DCASE sound anomaly dataset. Concluding, our anomaly score lays the foundations for an interpretable condition monitoring system.

1 INTRODUCTION

Renewable energy sources drive the energy transformation and are central for supply reliability. Applied machine learning and data mining methods carry the developments of the transitions in the energy sector (Arnoldt, 2010). The utilization of unsupervised methods has been a research area for wind turbines (Sheng, 2014) and multiple other application domains (Masino, 2017) (Bernhard, 2021/1) (Hofmockel, 2018). Anomaly detection with structure-born sound data describes detecting suspicious noises in a sound sequence that differs from the sound source's common character. Especially in machine condition monitoring, there is great economic potential because the standstill of complex production plants or wind turbines causes serious economic damage. Data acquisition is a near-impossible task, as the anomalous samples are sparse and usually highly diversified. As such, it is difficult to collect sufficient data samples from the anomaly class to comprehensively represent the intra-class variability and the unbalanced domains (Schutera, 2019). The notorious limitations of data acquisition and sparse target domains in machine learning (Bernhard, 2021/2) can be coped by unsupervised learning and encoding approaches (Schutera, 2020). In the field of acoustic anomaly detection, Gaussian mixture models (Dufaux, 2000), hidden Markov models (Chan, 2010), and support vector machines (Aurino, 2014) are common approaches. In recent years, neural networks have obtained superior results by modeling the regular, normal data samples with an encoder-decoder architecture (Koizumi, 2018) (Kawaguchi, 2017), using the reconstruction loss as a cue an anomaly measure. We show that with an algorithmic simple, density-based k-nearest neighbor method, we achieve high performance on two data sets, including different machine types and wind turbine data. Condition monitoring on wind turbine gearbox data has been of interest due to the significant downtime gearbox damages caused (Sheng, 2011/1). There are different data modalities for condition monitoring on wind turbine gearboxes, such as lubricant pressure (Wang, 2016), temperature monitoring (Feng, 2013), or performance monitoring

Bernhard, J., Schmidt, J. and Schutera, M.
Density based Anomaly Detection for Wind Turbine Condition Monitoring.
DOI: 10.5220/0011358600003355
In *Proceedings of the 1st International Joint Conference on Energy and Environmental Engineering (CoEEE 2021)*, pages 87-93
ISBN: 978-989-758-599-9

(Sharma, 2013). However, particular interest has been put into analyzing vibration signals (Zappala, 2014), which allow for direct sampling of structure-borne sound from gearbox components. For vibration data condition monitoring, amplitude analysis on specific frequency ranges can be used for automatic fault detection (Antoniadou, 2015). For online fault detection algorithms, in current work impulse analysis in the frequency spectrum has been proposed (Gong, 2014).

In detail, this work examines:

- A density-based k-nearest neighbor anomaly detection method for wind turbines and machine vibration data.
- The design and introduction of a sensor-level, frequency-based explainable anomaly score.

Especially in condition monitoring and predictive maintenance, the interpretability and explainability of anomaly scores are important and add value. By allowing insights into the nature and type of the detected anomaly, the explainability of the approach simplifies and supports the maintenance or other interventions to the monitored machines.

2 DATA

In real-world machine deployment, anomalous vibration signals are the exception and are of various kinds; this impedes data acquisition of anomalous samples. Therefore, the data sets for unsupervised detection of anomalous vibration signals are composed of a training set consisting of normal vibration samples only, a validation and test set consisting of normal and anomalous samples. In the following, we outline two data sets with these required characteristics.

2.1 NREL Wind Turbine

The wind turbine gearbox condition monitoring vibration analysis benchmarking data sets (Sheng, 2014) consists of data from a stall-controlled, three-bladed, upwind turbine with a rated power of 750kW (Sheng, 2011/2). The vibration data of the wind turbine is collected by three IMI 626B02 and five IMI 626B01 accelerometers, in $\frac{m}{s^2}$. Mounted on the outside of the gearbox. The sample rate is 40 kHz per sensor channel. The whole data set comprises ten healthy H (normal) vibration sequences of one minute each and ten damaged D (anomalous) vibration sequences of one minute each. Training is based on the sequences H1-H4. Validation is based on the sequences H5-H6 and D1-D2. For testing, the sequences H7-H10 and D3-D10 are deployed and evaluated.

2.2 DCASE2020 Anomaly Challenge Data Set

The unsupervised detection of anomalous sounds for machine condition monitoring data set (Koizumi, 2019) (Purohit, 2019) consists of data from six machine types (toy car, toy conveyor, valve, pump, fan, and Slider) with three to four machine instances. The whole data set comprises a training set of around 2000 (normal) sequences, a validation set of two times 100-200 (normal and anomalous) sequences, and a test set of around 400 (unlabeled) sequences for each machine instance. Each sequence represents an audio recording of around ten seconds.

3 ANOMALY DETECTION ARCHITECTURE

Anomaly detection is a data science discipline that focuses on finding outlier data points that indicate a significant deviation towards an underlying distribution. Hence, the model should learn features that describe patterns in the training data. The presence or absence of these patterns in the test data points helps estimating whether the point is part of the estimated distribution during training.

This paper uses a density-based anomaly detection method that incorporates a k-nearest neighbor search of frequency patterns. First, the data must be transposed into a fitting feature representation to create a metric space that is useful to the model. Transforming the sensor signals into a mel-spectrogram that comprises the vibration behavior on different frequency ranges serves this purpose. Afterward, forming a histogram with fixed bins for each frequency range converts the spectrogram data. The following subsections describe the model's workflow to set up a training library, depicted in figure 1.

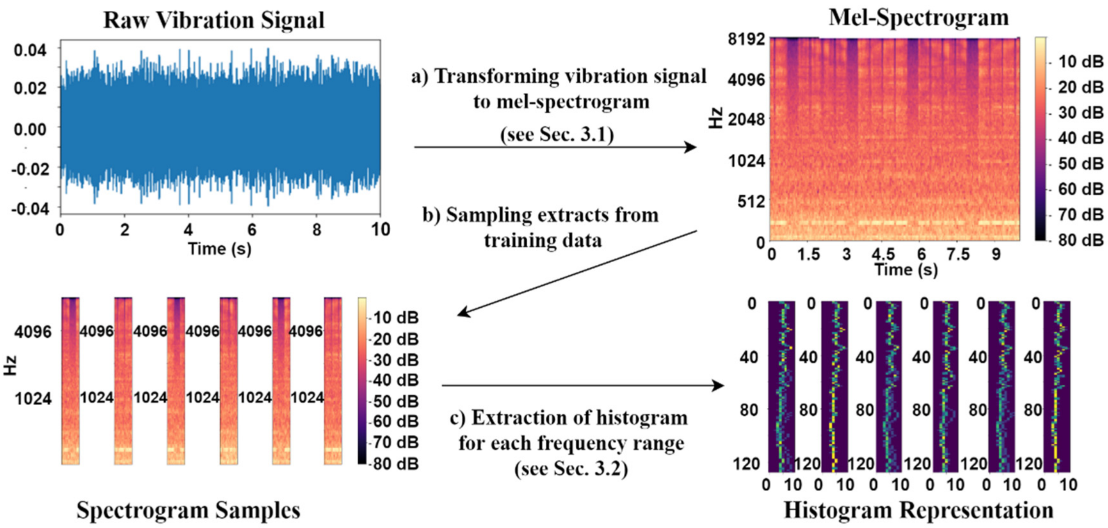

Figure 1. The feature extraction process for the training library. a) Vibration data files are transformed into spectrograms (mel-spectrogram processing) to provide a detailed representation of the frequency spectrum. b) A library (spectrogram sampling) that describes normal behavior, consisting of sampled short frames, is set up. c) Each frame translates into the feature representation by generating a histogram for each frequency bin (frequency band histogram feature extraction).

3.1 Data Preparation

The general audio classification approach extracts features from the temporal vibration signal specific to each class. Current state-of-the-art algorithms often use mel-spectrograms to transform the vibration signal from time to frequency domain. This time-frequency representation allows a good extraction of the frequency patterns and, at the same time, a dimensional reduction compared to a regular spectrogram. Log-mel-energies were by far the most popular feature in DCASE Task 4 (Serizel, 2019). For a mel-spectrogram, a Discrete Fourier Transform of the input signal is determined, and the power spectrum is converted to log-scale. A vibration signal of a previously defined window length is the input to calculate the DFT. This window then runs over the entire file to display the power spectrum change over time. Based on a person's relative perceived pitch, the frequencies are then converted into mel-scale, creating a mel-spectrogram (see figure 1a and figure 2). Since the frequency resolution is higher in the lower range and decreases for higher frequencies, this time-frequency representation is particularly suitable for machine condition monitoring. Most of the observed signal's energy is in the lower range. Finally, the spectrograms for each type of machine are normalized.

3.2 Feature Extraction

The underlying assumption for the anomaly detection method in this paper is that the vibration data of damaged wind turbines will have intensities in different frequency ranges than the vibration data of healthy wind turbines. Hence, if over a given time frame, for normal and anomalous data, a histogram for a given frequency range displays different value distributions. Therefore, calculating the distance between their histograms for each frequency range yields the spectrograms' similarity. The model focuses on small extracts with length l along the entire spectrogram's time axis, subsequently denoted frames (see figure 1b). Hence, with frame length l, a spectrogram $\boldsymbol{S}$ of size $f \times n$, where f denotes the number of frequency bins, and n denotes the total number of time steps, can be cut into a maximum of $n - l + 1$ frames $\boldsymbol{E}$ of size $f \times l$. To create a feature representation of the value distribution for a given frame and frequency range $i \in \{1, \ldots, f\}$, a histogram $\boldsymbol{h}_{i,b}$ of row i with b bins is generated (see figure 1c). The maximum and minimum intensity observed on the frequency range of i in the training data equal each histogram's maximum and minimum values. Therefore, a frame $\boldsymbol{E}$ of size $f \times l$ is used to generate a histogram matrix $\boldsymbol{H} = \{\boldsymbol{h}_{1,b}, \ldots, \boldsymbol{h}_{f,b}\}^T$ of size $f \times b$.

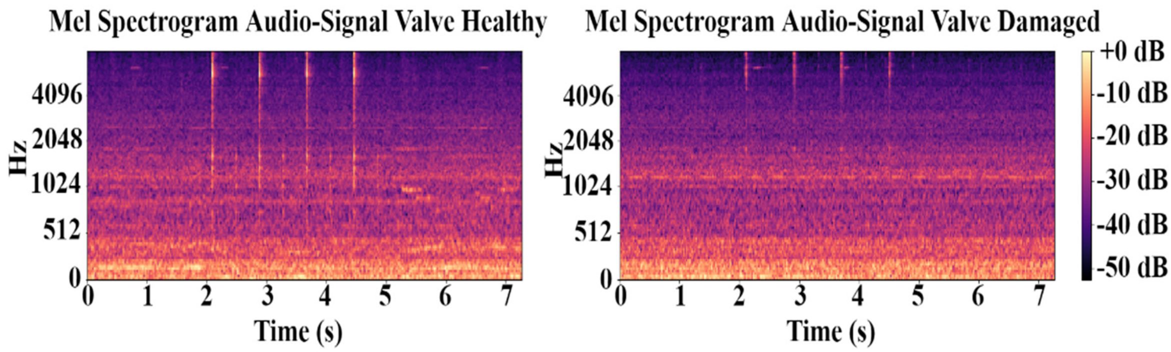

Figure 2. Mel-spectrogram of audio data depicted as frequency (Hz) over time (s). A comparison of healthy and damaged valve audio data shows the signal's energy distribution difference.

3.3 Anomaly Score Calculation

To apply a k-nearest neighbor search (see equation (1)) for anomalies, a set of training features must be generated describing normal vibration behavior. This is done by uniformly sampling v data points from the set of all training data frames and converting the sampled frames to histogram matrices that are added to the training library $\mathcal{L} = \{\boldsymbol{H}_i\}_{i\in\{1,\ldots,v\}}$. To get the anomaly value of a test frame, the frame is transformed into the histogram matrix $\widetilde{\boldsymbol{H}}$. The anomaly score is then calculated as the average distance to the k-nearest neighbors:

$$A = \frac{1}{k}\sum_{i=1}^{k} O(\boldsymbol{d})_i \qquad (1)$$

with $d_i = ||\widetilde{\boldsymbol{H}} - \boldsymbol{H}_i||_2$ being the distance vector from $\widetilde{\boldsymbol{H}}$ to $\mathcal{L}$ and $O(\boldsymbol{d})$ being a function that arranges the distance vector $\boldsymbol{d}$ in ascending order. For calculating the anomaly score of a whole test-spectrogram, the anomaly scores of each frame are evaluated and averaged.
The whole process of calculating the anomaly score for a test sequence $\boldsymbol{x}$ of arbitrary length is expressed by the function $M(\boldsymbol{x})$.

3.4 Anomaly Detection Metrics

Metrics for benchmarking anomaly detection systems are Area Under Curve (AUC, see equation (2)) and partial Area Under Curve ($pAUC$, see equation (3)), which are independent of decision rules and thus provide a reliable measure for anomaly detection. We divide the set of test data in $\mathcal{N}_-$ (normal) and $\mathcal{N}_+$ (anomalous) test data. Let $\{\boldsymbol{x}_i^-\}_{i=1}^{N_-}$ and $\{\boldsymbol{x}_i^+\}_{i=1}^{N_+}$ be the normal and anomalous test sequences in descending order of their average anomaly score. By using the flooring function $\lfloor\cdot\rfloor$ and the step function $G(\cdot)$, which is 1 when the input is above 0, and 0 otherwise, the metrics are defined as:

$$AUC = \frac{1}{\mathcal{N}_-\mathcal{N}_+}\sum_{i=1}^{\mathcal{N}_-}\sum_{j=1}^{\mathcal{N}_+} G\left(M(x_j^+) - M(x_i^-)\right) \qquad (2)$$

$$pAUC = \frac{1}{\lfloor p\mathcal{N}_-\rfloor\mathcal{N}_+}\sum_{i=1}^{\lfloor p\mathcal{N}_-\rfloor}\sum_{j=1}^{\mathcal{N}_+} G\left(M(\boldsymbol{x}_j^+) - M(\boldsymbol{x}_i^-)\right) \qquad (3)$$

We choose $p = 0.1$ and thus estimate how high the probability is that our model, with a false positive rate of a maximum of 10%, predicts for a random normal test sample a lower anomaly score than for a random anomalous test sample.

4 EXPERIMENTS

The NREL wind turbine data set is split into training and validation data, as detailed in section 2. Each of the nine sensor channels initiates the training of a sensor channel-specific model. Hence, for each time frame, there are nine individual anomaly scores. Averaging the anomaly scores provides the evaluation of the wind turbine's cumulative behavior.

4.1 Training Parameters

The model's performance relies on a set of hyperparameters that can be adjusted: Number of mels f specifies the number of mel-bins, indicating the frequency resolution on the mel-scale. We use an fft-length of 1024 with hop size 512 and a Hanning window (Gautam, 1996). Extract length l specifies the number of time steps that are included in one frame.

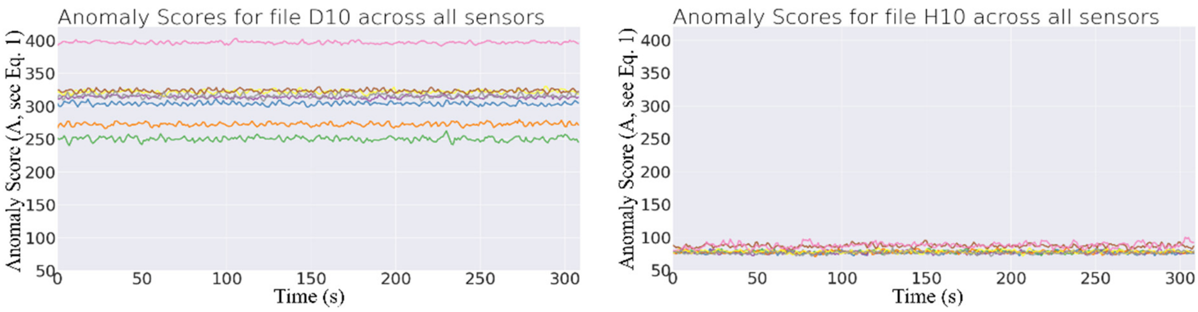

Figure 3. Anomaly scores across the sensors with different mounting positions [2] for damaged and healthy wind turbine data. The sensors' emerging anomaly pattern potentially supports during troubleshooting and hints at specific failure cases.

During extraction of the frames, we used a stride parameter of 15 that defines the number of time steps the window is shifted for the next frame. While a high l allows to reduce noise and focus on periodic patterns, it also bears the risk of significant anomalous spikes being vanished by normal behavior before and after. Number of histogram bins b specifies the resolution of the intensity distribution. Choosing b allows adjusting the model's sensitivity towards noise. Number of nearest neighbors k specifies the number of training data points for the anomaly score evaluation. The hardware setup for training, inference, and evaluation consisted of an NVIDIA Tesla P100 GPU (16GB GPU memory).

5 RESULTS

5.1 Anomaly Detection Performance

Deployed on the NREL wind turbine data, the model distinguishes between healthy and damaged samples. Figure 3 depicts the anomaly scores for damaged and healthy wind turbine data across all sensor types. Table 1 shows the averaged anomaly scores for each sequence with the respective standard deviation. The model achieves a clear delineation between the anomalous (anomaly scores approx. 310, see table 1) and healthy samples (anomaly score approx. 78, see table 1) of the wind turbine.

Furthermore, the model achieves AUC scores above 70% and pAUC scores above 65% across all machine types and IDs on the DCASE2020 data set (see table 2). Especially machine toy car experiences robust results, while the machine valve poses a challenge to the proposed model. The model outperforms the deep-learning baseline model on every machine other than slider.

5.2 Model Interpretability

Our model's implementation on the wind turbine data allows evaluating the vibration behavior on sensor-level (see figure 3). High anomaly scores on specific sensors indicate damage location. Our model supports interpretable anomaly scores in contrast to deep learning-driven anomaly detection approaches, such as auto-encoders. High scores can be tracked down to and explained by the distribution of intensity values on specific frequency ranges and individual sensors. Tracking allows the analysis of anomalous patterns and the comparison with previous occurrences. Hence, the model detects general anomalies and lays the foundation for anomaly classification and prediction.

Table 1. Anomaly score estimation for wind turbine data. Scores are averaged across sensor types and time steps. There is a clear delineation between the anomaly scores for healthy wind turbine recordings and the anomaly scores for damaged wind turbine recordings. Training parameters: $l = 128, f = 40, b = 8, k = 4.$

	H7	H8	H9	H10	D3	D4	D5	D6	D7	D8	D9	D10
mean	77.0	77.3	78.0	79.4	309.1	313.4	308.7	305.8	311.7	310.9	313.9	311.9
Std.	±1.01	±0.96	±1.26	±0.88	±1.03	±1.01	±0.92	±1.05	±1.05	±1.10	±1.05	±0.92

Table 2. Performance comparison between the proposed model and the DCASE2020 Challenge 2 baseline model (Koizumi, 2020). They implemented a classical deep-learning auto-encoder approach to find anomalous behavior in the sound files. As a result, the model manages to achieve a significant anomaly detection performance on each machine. Furthermore, the model outperforms the baseline model on every machine type except slider.

	Proposed Model (ours)		**Baseline**			**Proposed Model (ours)**		**Baseline**	
	AUC (%)	pAUC (%)	AUC (%)	pAUC (%)		AUC (%)	pAUC (%)	AUC (%)	pAUC (%)
Toy Car	*f = 128*	*l = 75*	*b = 10*	*k = 2*	**Toy Conveyor**	*f = 128*	*l = 70*	*b = 5*	*k = 2*
ID 1	95.6	80.6	81.4	68.4	***ID 1***	87.1	71.0	78.1	64.3
ID 2	98.9	94.5	86.0	77.7	***ID 2***	67.2	52.4	64.2	56.0
ID 3	92.5	78.1	63.3	55.2	***ID 3***	79.2	66.7	75.3	61.0
ID 4	98.9	96.6	84.5	69.0	**Average**	77.8	63.4	72.5	60.4
Average	96.4	87.5	78.8	67.6					
Fan	*f = 128*	*l = 75*	*b = 7*	*k = 4*	**Pump**	*f = 128*	*l = 70*	*b = 7*	*k = 4*
ID 1	60.5	51.9	54.4	49.4	***ID 1***	76.2	55.4	67.2	56.7
ID 2	89.5	65.9	73.4	54.8	***ID 2***	83.6	75.8	61.5	58.1
ID 3	78.3	58.9	61.6	53.3	***ID 3***	94.1	77.1	88.3	67.1
ID 4	81.1	57.0	73.9	52.4	***ID 4***	78.7	57.5	74.6	58.0
Average	77.3	58.4	65.8	52.5	**Average**	83.2	66.4	72.9	56.0
lider	*f = 128*	*l = 75*	*b = 5*	*k = 5*	Valve	*f = 128*	*l = 35*	*b = 10*	*k = 1*
ID 1	98.5	93.7	97.0	81.4	***ID 1***	74.1	55.3	68.8	51.7
ID 2	81.6	65.5	79.0	63.7	***ID 2***	68.7	51.8	68.2	51.8
ID 3	83.0	55.0	94.3	72.0	***ID 3***	75.2	51.4	74.3	52.0
ID 4	60.9	51.2	69.6	49.0	***ID 4***	62.8	48.6	53.9	48.4
Average	81.0	66.3	84.8	66.5	**Average**	70.2	51.8	66.3	51.0

6 DISCUSSION

We introduce a method for effective fault detection on vibration data with this work. The proposed method uses spectrogram transformations of the input signal to automatically extract healthy signals' characteristics over the whole frequency spectrum by building histogram representations. The analysis pipeline can identify the core frequency windows and characteristics without prior knowledge of the underlying mechanical system.

Using the k-nearest neighbor anomaly detection method, the systems deployment signals are examined for damages or malfunctions. This method was tested on sound signals and vibration signals to prove its viability.

There is a range of potential future work to improve the presented approach: Starting with deploying the approach to related areas, such as premature fault prediction or supervised fault classification by comparing the extracted features of deployment data to previously observed features. Another extension introduces the ability to recognize long-term dependencies by estimating conditional distributions. Not only recognizing anomalous frequency patterns but also anomalous sequences of frequency patterns.

We are confident that this work supports practitioners when deploying condition monitoring or predictive maintenance algorithms[1]. Further, we hope to stimulate research on overcoming the restrictions imposed by unbalanced domains in acoustic anomaly data sets while ensuring interpretability.

[1] An interactive implementation of the model can be found in: https://github.com/VanLock9988/Vibration_Data_Anomaly_Detection

REFERENCES

Antoniadou, I., Manson, G., Staszewski, W. J., Barszcz, T., & Worden, K. (2015). A time-frequency analysis approach for condition monitoring of a wind turbine gearbox under varying load conditions. (Elsevier, Ed.) Mechanical Systems and Signal Processing, 64, 188-216.

Arnoldt, A., König, S., Mikut, R., & Bretschneider, P. (2010). Application of Data Mining Methods for Power Forecast of Wind Power Plants. Proc., 9th International Workshop on Large-scale Integration of Wind Power and Transmission Networks for Offshore Wind Farms, Quebec.

Aurino, F., Folla, M., Gargiulo, F., Moscato, V., Picariello, A., & Sansone, C. (2014). One-class SVM based approach for detecting anomalous audio events. International Conference on Intelligent Networking and Collaborative Systems, (pp. 145-151). IEEE.

Bernhard, J., Schulik, T., Schutera, M., & Sax, E. (2021/2). Adaptive test case selection for DNN-based perception functions. IEEE International Symposium on Systems Engineering (ISSE), (pp. 1-7). IEEE.

Bernhard, J., Schutera, M., & Sax, E. (2021/1). Optimizing test-set diversity: Trajectory clustering for scenario-based testing of automated driving systems. IEEE International Intelligent Transportation Systems Conference (ITSC), (pp. 1371-1378). IEEE.

Chan, C. F., & Eric, W. M. (2010). An abnormal sound detection and classification system for surveillance applications. 18th European Signal Processing Conference, (pp. 1851-1855). IEEE,

Chang, F. K., Markmiller, J. F., Yang, J., & Kim, Y. (2011). Structural health monitoring. System health management: with aerospace applications. John Wiley & Sons.

Dufaux, A., Besacier, L., Ansorge, M., & Pellandini, F. (2000). Automatic sound detection and recognition for noisy environment. 10th European Signal Processing Conference. IEEE.

Feng, Y., Qiu, Y., Crabtree, C. J., Long, H., & Tavner, P. J. (2013). Monitoring wind turbine gearboxes. (W. O. Library, Ed.) Wind Energy, 16(5), 728-740.

Gautam, J. K., Kumar, A., & Saxena, R. (1996). On the modified Bartlett-Hanning window (family). IEEE Transactions on Signal Processing, 44(8), 2098-2102.

Gong, X., & Qiao, W. (2014). Current-based mechanical fault detection for direct-drive wind turbines via synchronous sampling and impulse detection. (IEEE, Ed.) IEEE Transactions on Industrial Electronics, 62(3), 1693-1702.

Hofmockel, J., & Sax, E. (2018). Isolation Forest for Anomaly Detection in Raw Vehicle Sensor Data. International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS).

Kawaguchi, Y., & Endo, T. (2017). How can we detect anomalies from subsampled audio signals? 27th IEEE International Workshop on Machine Learning for Signal Processing (MLSP), (pp. 1-6). IEEE.

Koizumi, Y. a. (2018). Unsupervised detection of anomalous sound based on deep learning and the neyman- pearson lemma. IEEE/ACM Trans-actions on Audio, Speech, and Language Processing. 27(1), 212-224.

Koizumi, Y., Saito, S., Uematsu, H., Harada, N., & Imoto, K. (2019). ToyADMOS: A dataset of miniature-machine operating sounds for anomalous sound detection. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA), (pp. 313-317). IEEE.

Koizumi, Y., Kawaguchi, Y., Imoto, K., Nakamura, T., Nikaido, Y., Tanabe, R., ... & Harada, N. (2020). Description and discussion on DCASE2020 challenge task2: Unsupervised anomalous sound detection for machine condition monitoring. arXiv preprint arXiv:2006.05822.

Masino, J., Pinay, J., Reischl, M., & Gauterin, F. (2017). Road surface prediction from acoustical measurements in the tire cavity using support vector machine. Applied Acoustics, 125 41-48.

Purohit, H., Tanabe, R., Ichige, K., Endo, T., Nikaido, Y., Suefusa, K., & Kawaguchi, Y. (2019). MIMII Dataset: Sound Dataset for Malfunctioning Industrial Machine Investigation and Inspection. Proceedings of the Detection and Classification of Acoustic Scenes and Events 2019 Workshop (DCASE2019), (pp. 209-213).

Schutera, M., Hafner, F. M., Vogt, H., Abhau, J., & Reischl, M. (2019). Domain is of the Essence: Data Deployment for City-Scale Multi-Camera Vehicle Re-Identification. 16th IEEE Inter-national Conference on Advanced Video and Signal Based Surveillance (AVSS). (pp 1-6). IEEE.

Schutera, M., Hussein, M., Abhau, J., Mikut, R., & Reischl, M. (2020). Night-to-Day: Online Image-to-Image Translation for Object Detection Within Autonomous Driving by Night. IEEE Trans-actions on Intelligent Vehicles.

Serizel, R., & Turpault, N. (2019). Sound event detection from partially annotated data: Trends and challenges. IcETRAN conference.

Sharma, S., & Mahto, D. G. (2013). Condition monitoring of wind turbines: a review. Global Journal of Researches in Engineering, Mechanical and Mechanics Engineering, 13(6).

Sheng, S. (2011/2). Investigation of various condition monitoring techniques based on a damaged wind turbine gearbox (No. NREL/CP-5000-51753). National Renewable Energy Lab.(NREL), Golden, CO (United States).

Sheng, S. (2014). Wind turbine gearbox condition moni-toring vibration analysis benchmarking datasets. National Renewable Energy Laboratory, Golden.

Sheng, S., Link, H., LaCava, W., van Dam, J., McNiff, B., Veers, P., ... & Oyague, F. (2011/1). Wind turbine drivetrain condition monitoring during GRC phase 1 and phase 2 testing (No. NREL/TP-5000-52748). National Renewable Energy Lab.(NREL), Golden, CO (United States).

Wang, L., Zhang, Z., Long, H., Xu, J., & Liu, R. (2016). Wind turbine gearbox failure identification with deep neural networks. IEEE Transactions on Industrial Informatics, 13(3), 1360-1368.

Zappalá, D., Tavner, P. J., Crabtree, C. J., & Sheng, S. (2014). Side-band algorithm for automatic wind turbine gearbox fault detection and diagnosis. (W. O. Library, Ed.) IET Renewable Power Generation, 8(4), 380-389.