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Signal processing informed deep learning for failure detection in a fleet of multi-stage planetary gearboxes with limited knowledge about characteristic frequencies

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Abstract

Condition monitoring of multi-stage planetary gearboxes is a complex challenge given the fact that gears the large number of rotating subcomponents. Typically, the large number of gears creates many harmonic excitations masking bearing signatures. Different state-of-the-art harmonic removal methods, e.g. cepstrum liftering, are available. Such methods have been shown to be automatable. However, exact characteristic frequency values are not always known for such gearboxes in commercial systems. Estimation of gear teeth numbers has been shown in literature. Bearing frequency determination is much more challenging. Deep learning methods can offer a solution. Once the harmonic content is removed, focus can be on the detection of modulations linked to bearing problems. Spectral coherence methods have shown to be highly reliable for such detection. However, if no info is available about normal behaviour in the coherence maps it is essential to detect which modulations are changing over time. This paper investigated the use of deep learning auto-encoders trained on spectral coherence maps as core component in an anomaly detection framework to identify changes in modulations. The auto-encoders are trained with large sets of healthy data. In this way we maximally use available data and avoid the need of large sets of labelled failure data. Typically, such data is not available for most operators. To illustrate the methodology data of six offshore wind turbines is used.

Keywords: Planetary gear, condition monitoring, vibration, deep learning, physics-informed

Introduction

Condition monitoring (CM) targeting fast and accurate detection of problems is an important aspect in a typical predictive maintenance strategy, since the logistics of spare parts and repair equipment (e.g. crane vessels for wind turbines [1]) need to be optimized to avoid large downtimes. Faults need to be detected early to allow for alarming. However, providing a general alarm as a diagnostics feature does not suffice. CM methods need to be able to distinguish between the fault types and pinpoint the analyst to the subcomponent that needs to be replaced. Typically, the characteristic frequencies linked to the rotational fault signature are used for this purpose. Nonetheless, many end-users of machines have limited access to the details of these frequencies as they are not always disclosed by the manufacturer or different machine variants can have slightly different subcomponents (e.g. bearings). In literature, methods exist to estimate the characteristic frequencies linked to gear teeth numbers. An example is the method of Sawalhi and Randall targeting the use of a fine-tuned harmonic-sideband cursor approach [2]. For the estimation of bearing fault frequencies these methods are existing much less. An important aspect to this is that bearings typically experience a non-deterministic nature due to the slippage of the rolling elements. Another challenge is that healthy bearings typically do not show fault frequencies. As such the healthy data is not useful for a bearing frequency estimation approach. Bearing frequency agnostic methods are needed that can learn the behaviour of a healthy vibration signal and alarm upon changes specifically linked to faults. This paper targets such a methodology by leveraging deep learning methods in combination with advanced signal processing methods.

Methodology

The proposed methodology targets a multi-step learning approach that can classify data according to healthy and faulty behaviour and pinpoint to the fault type present in the system. These steps are schematically shown in Fig. 1 and are discussed in the following subsections.

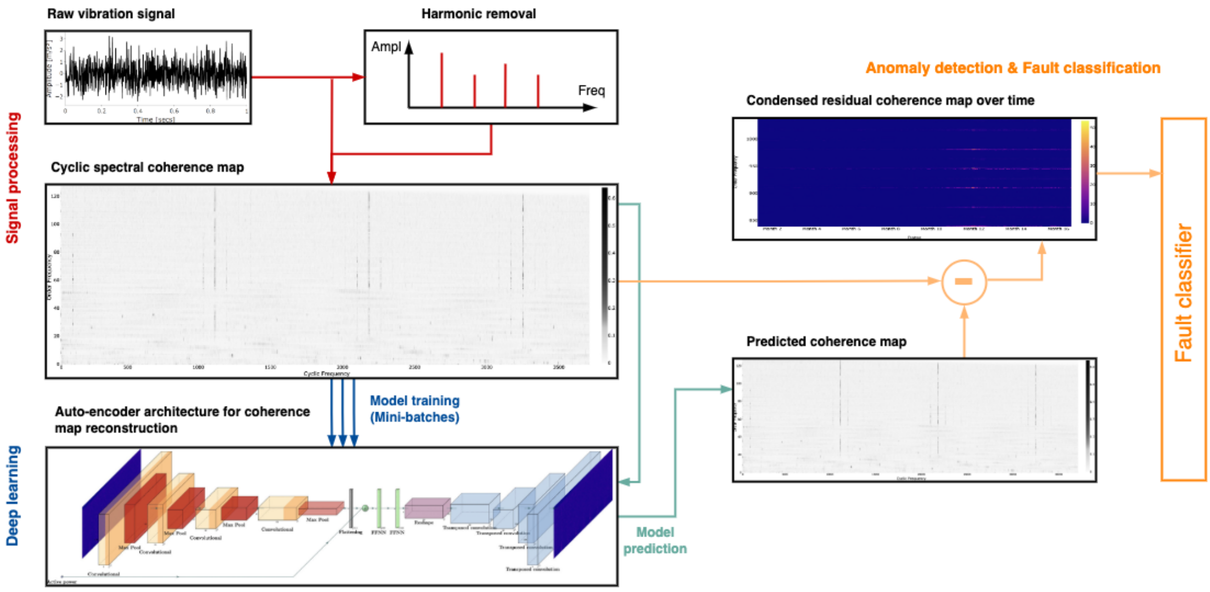

Fig. 1: Schematic overview of the fault detection and classification approach.

Signal processing

Complex gearboxes contain multiple gear stages resulting in many harmonic disturbances. These mask the bearing content and need to be removed to allow further diagnostics targeted towards bearing faults. Two possible harmonic removing methods that we explored in this context are: cepstrum based harmonic removal [3,4,5] and cepstrum pre-whitening [4,6]. In the former, discrete quefrencies are removed by means of a harmonic lifter. This requires knowledge about the characteristic gear frequencies. Thus, this is only possible if this information was retrieved (e.g. using a harmonic-sideband cursor). In case this information is not available, the cepstrum can be liftered by means of a pre-whitening approach. This method sets the whole real cepstrum to zero, except for zero quefrency. For this paper, we opt for a cepstral pre-whitening approach. This step is optional in case the harmonic orders do not substantially disturb the spectral coherence map constructed in the next part of the signal processing.

Subsequently, the cyclo-stationary properties of the signal are extracted by constructing the two-dimensional cyclic spectral coherence map [7]. The magnitude of the spectral coherence ranges from 0 to 1 and forms a very useful detection method for second-order cyclo-stationary signatures. As such it can be seen as the spectral correlation of the whitened signal. The coherence map allows for the tracking of the amplitude of the candidate modulating frequencies linked to the potential characteristic fault frequencies of gears and bearings. In this paper we opt to extract changes at these frequencies by means of an anomaly detection approach that compares actual coherence maps to predicted coherence maps using the deep learning approach discussed in the next subsection.

Deep learning

For the prediction of the coherence maps we use CNN based autoencoders. Such an unsupervised deep learning method first encodes the input data to a compressed representation. In a second step it decodes the compressed representation to obtain a reconstruction of the input. Thus, the autoencoder consists of three parts: the encoder, feature representation, and decoder. The autoencoder cannot perfectly reconstruct the input. Depending on the complexity of the underlying learning network and the amount of training data used, the autoencoder is able to capture and thus reconstruct fewer or more characteristics of the input signal.

Training approach

At the start of the training process the node weights are randomly initialized. Then, a forward pass is done for each mini-batch of coherence maps using the current weights. A reconstruction of that mini-batch is obtained as output. The error is calculated between the original and reconstructed mini-batch. The mean square error is used as loss function to minimize:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - g(f(x_i)))^2 \quad (1)$$

This error is propagated backward and the contribution of each of the weights to the error determined. The weights are updated by means of the gradient descent method.

Anomaly detection

Finally, the deep learning model needs to be part of an anomaly detection and fault classification framework. The autoencoder is an unsupervised learning method. It allows to generate an expected coherence map. This expected behaviour is compared to the actual coherence map to generate a residual map. For each time instance the residual maps are combined into one residual map over time with on the ordinate the order frequencies and on the abscissa time.

Thresholding within this residual map allows to identify changes in modulations linked to characteristic frequencies of bearings and gears. The threshold values are determined by the maximum residual values under normal machine operation.

Fault classification

As mentioned in the introduction, not all operators have access to the characteristic frequencies of the machine. This implies that modulations can be identified by the proposed methodology, but they need to be classified to gain insights in their potential meaning. To allow for this fault classification an engineering rules framework is used. We encode the knowledge that we have about the system. First of all, we know the speed of the system. In case no true highly detailed encoder is available such speed information can be derived from the acceleration signal itself [8]. This allows to classify detected modulations from non-speed related behaviour. Typically, this step will reduce most of the random anomalies from interesting ones. Second, we aim for cyclic orders that are present at different carrier frequency bands. This classifier step allows to distinguish further between strongly pronounced modulations and increases thus confidence that indeed a fault is present. It should be noted that the certainty is strongly linked to the amount of information that the user has about the system itself. The fewer details, the more difficult to pinpoint to a specific subcomponent of the overall system.

Experiments

The proposed method is validated by means of data from six offshore multi-megawatt wind turbines. The rated power of the machines is in the range of 2-4MW. Three years of data is available with measurements taken under stable conditions for a wide variety of operating conditions spanning the wind turbine power curve. Data is collected for 10s at a sampling frequency over 20kHz. We use more than 100 data samples per turbine per year for the analysis.

One turbine experienced an intermediate speed stage fault. This case is used to validate the detection potential of the method. Five turbines are healthy and serve as benchmark for method robustness against false positives.

To train the autoencoder model 3624 coherence maps are used (about 80% of the dataset of the five healthy turbines). 20% of the dataset of the 5 healthy turbines is used for validation of the model quality to represent healthy behaviour. The mini-batch size is 16. To determine the thresholds for anomaly alarms in the condensed residuals coherence map over time the 99th percentile for the training dataset is determined.

Faulty case

Fig. 2 shows the results for the intermediate stage fault. The figure represents the alarming plot versus time based on the residuals generated by the anomaly detection framework. The fault classification identifies that after month 11, the BPFI order of 946 is clearly visible as well as integer multiples. This increases confidence that indeed a fault is present. In this case we can link this to the specific fault in the system. If no detailed characteristic frequencies are known, it is still possible to identify this situation as a fault. However, pinpointing to the exact problem difficult.

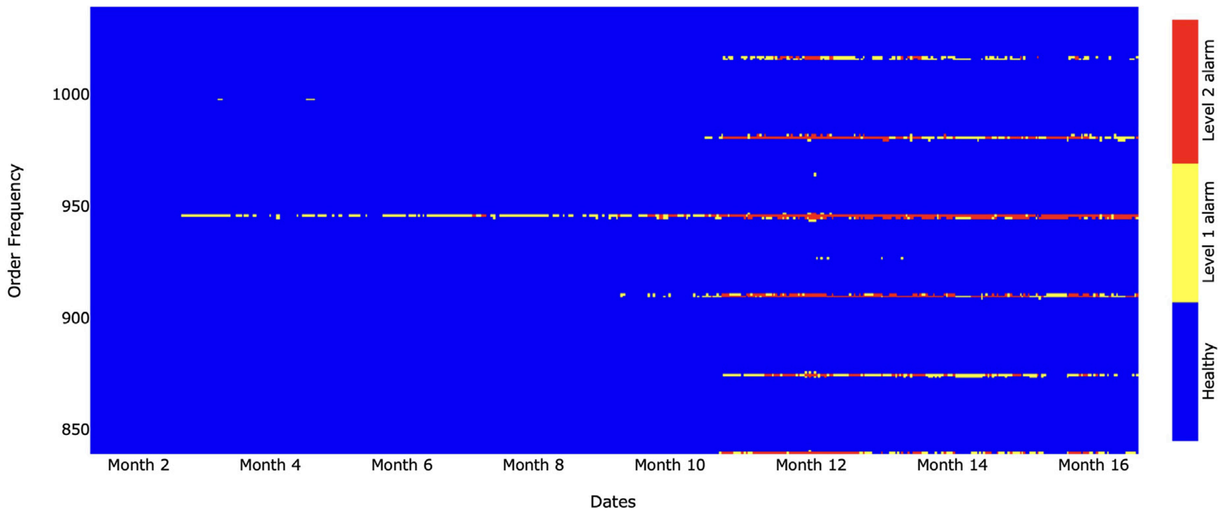

Fig. 2: Alarm map for the faulty turbine case. The red points represent alarm level 2, the yellow points alarm level 1 and the blue points healthy behaviour

Healthy cases

Fig. 3 shows an example of a healthy case. It is clear that no consistent orders are marked in the alarm graph and thus that no fault is present. This was the same for the other healthy cases and underpins the robustness of the approach.

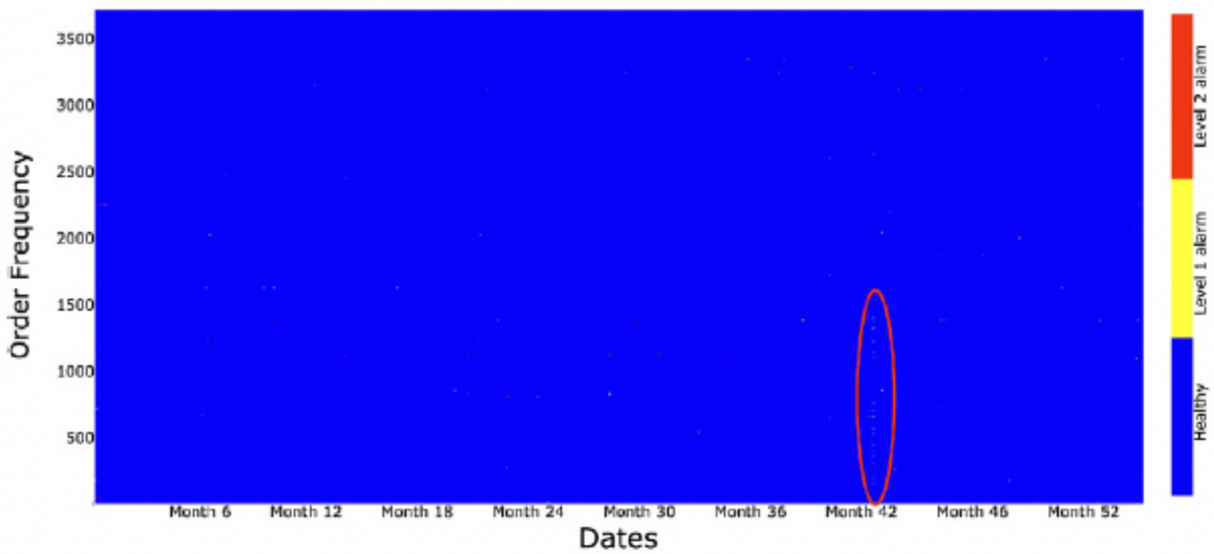

Fig. 3: Alarm map for one of the healthy turbine cases. The red points represent alarm level 2, the yellow points alarm level 1 and the blue points healthy behaviour

Conclusions

This paper provided a method for the determination of bearing faults in an automated way. The method was a hybrid exploiting signal processing methods with deep learning using autoencoders. The method combined unsupervised learning using anomaly detection with a fault classification approach to automatically classify faults based on engineering insights. Depending on the amount of known information about the system (e.g. characteristic frequencies) the method can provide insights in which subcomponent the fault is present.

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