20th Australian International Aerospace Congress

ISBN number: 978-1-925627-66-4

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An industrial unsupervised Machine Learning model combined with a signal processing approach to detect failures in complex rotating assemblies

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Abstract

To deploy Health Condition Monitoring (HCM) systems, which aim to realise early warning, alarm and anomaly detection according to online data, there are numerous signal processing methods to extract relevant information. Machine Learning techniques also appear in a growing literature to avoid handcrafted analysis. However, they are challenging to train as they require a large amount of labelled data representing healthy and non-healthy conditions. Notably, applying purely data-oriented algorithms in an industrial context is challenging due to a shortage of data from a machine running in an unhealthy state.

To address this challenge, an innovative framework is proposed, which is based on an unsupervised machine learning framework combined with advanced signal processing techniques, for detecting cyclo-stationary phenomena, well suited for rotating machines. This framework is applied to publicly available datasets, showing very promising results on early failure detection without training labelled data, i.e. only based on the indication of healthy condition status.

Finally, the framework is applied to the HUMS2023 Data Challenge to detect as early as possible, the planet gear crack before its propagation causes catastrophic consequences.

Keywords: Health Condition Monitoring (HCM), Unsupervised Deep Learning, Detection of Cyclo-stationary signals.

Introduction

As planetary transmission systems become more and more widely used in complex mechanical systems such as heavy trucks and helicopters, there is a significant research interest in Prognostics and Health Management (PHM) and, in particular, in Health Condition Monitoring (HCM) which aim to realize early warning, alarm and anomaly detection according to online data. There are numerous methods to extract time or time-frequency-based diagnostic features from input vibration signals, such as mean, RMS, Skewness, Kurtosis, and spectral diagrams. Machine Learning techniques also appear in a growing literature to avoid handcrafted analysis. However, they are challenging to train as they require a large amount of labelled data representing healthy and non-healthy conditions. Notably, applying purely data-oriented algorithms in an industrial context is challenging due to a shortage of data from a machine running in an unhealthy state.

IoT Consultants initiated an R&D program to address this challenge by proposing an innovative framework based on an unsupervised machine learning framework with advanced signal processing techniques, including recently advanced signal processing algorithms for detecting non-stationary phenomena, well suited for rotating machines.

This paper is organised as follows. First, the framework of combined signal-processing / machine learning approach is presented. Then, the detection scheme is applied to two several publicly available datasets: the rolling element bearing dataset of the Center for Intelligent Maintenance Systems (IMS) of the University of Cincinnati and the Case Western Reserve University (CWRU) bearing data center dataset. After, the methodology is deployed to the HUMS2023 Data Challenge to detect as early as possible, the planet gear crack before its propagation causes catastrophic consequences. Finally, concluding remarks are given for future research and improvements of our system.

Framework

The proposed innovative Health Condition Monitoring framework relies on key concepts related hereafter trough existing work.

To perform vibration monitoring of rotating machines, it is now well recognised that Spectral Kurtosis (SK) can be used to detect non-stationary or transient signals caused by faulty elements, such as rolling bearing, slightly more efficiently than the global Kurtosis alone or the power spectral density applied to accelerometers raw data (see. eg. [1]). However, an optimal frequency resolution Δf has to be selected to detect those elements of interest. In this context, an exploratory tool for non-stationary signals was introduced by Antoni J. (see [2] and [3]) who called it Kurtogram, which is a map, formed by SK as a function of frequency f and frequency resolution Δf. For example, in [2], the author presents an application for rolling element bearing diagnostics. The Kurtogram indicates if there are abnormal transients in the signal (due to high values of Kurtosis) and for which frequency they occur. Depending on the level of details, a Kurtogram gives insights for analysing the causes of observed transient signals, such as: bearing crack on inner race (BCI), bearing crack on outer race (BCO), etc... The second example given in [2] is the detection of wandering bodies in nuclear plant piping which also induce transient or cyclo-stationary signals.

In cases of rotating machines, as Kurtograms can be considered as n x m images with useful information representing the status of the considered system, in particular when specific high Kurtosis values reveal the presence of damages, Deep Learning methods can be deployed to identify whenever a system is going to fail. For images, it it now well admitted that Convolutional Neural Networks (CNN) are very well suited for scene or object detection. This idea of their application to Kurtograms was first developed in [4] and [5]. Given a labelled dataset, representing healthy and multiple faulty conditions, the CNN, after being trained, is able to give a probability to face a given situation, among multiple classes, with an interesting accuracy (over 95%). It is worth noting that CNN presents the advantage to be trained in several running environments, as it is the case for example for [4], for multiple shaft speeds.

CNN, combined with Kurtograms, are clearly efficient to reduce the state space, instead of considering direct rows data of accelerometers, which could become very huge, for example, at 20Khz acquisition rate, to be compared with 12 x 144 Kurtograms' images at level 6 (which needs less than 10K accelerometer output values).
In addition, this preprocessing phase leads to provide smoothed and normalized data which prepares and highlights shapes of interest, similarly to shapes in common objects or dogs and cats images usually used in the literature to design and to challenge new deep learning algorithms (as a result, there are many publicly datasets, related to common objects).

Embedded in real time systems, these Deep Learning techniques avoid handcrafted analysis but remain challenging to train as they require a huge number of labelled datasets, which are not necessarily available, especially for new systems, which, by definition, have not yet failed. In the literature, there are some augmentation techniques, aiming to complete data, especially unbalanced data, such as [6], using Generative Adversarial Neural (GAN) networks to create artificially raw accelerometer data corresponding to a given (trained) condition.

Another approach, proposed in this paper, is to notice that most of the time, systems spend their time in healthy conditions, possibly in multiple operating conditions, such as loads or speeds. As a result, a huge amount of data is available and unsupervised machine techniques can be applied to learn patterns under these “normal conditions”. Then, if a degraded condition appears, which was not learnt by the algorithm, the classifier is able to detect this abnormal situation, and further investigation can be undertaken. Obviously, this methodology is relevant if the algorithm detects this possibly faulty conditions as earlier as possible.

This idea of this unsupervised methods was developed in [7] and [8], in which GANs are deployed, using directly raw accelerometer data, after eventually applying a Time Synchronous Averaging (TSA) algorithm on Gearboxes.

We propose to use this key concept, but, instead of considering raw data, Kurtograms, presented above, are used to feed GANS. The general overview of the framework is presented in Figure 1 below.

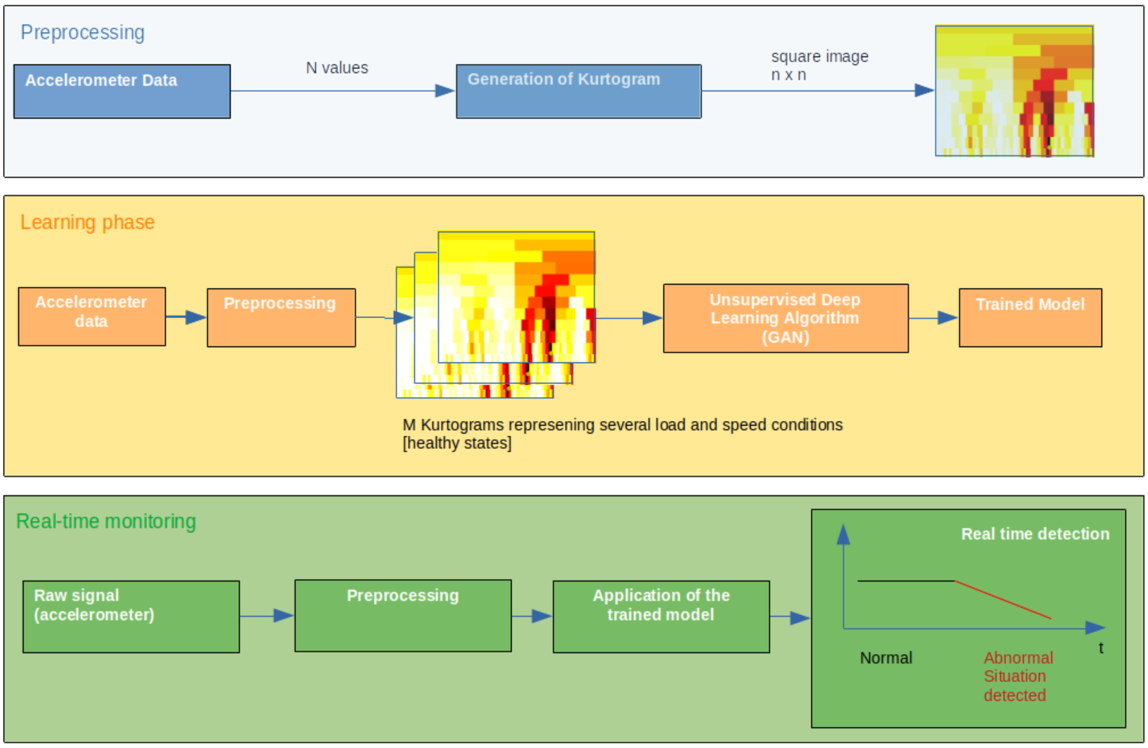

Figure 1: Framework overview

Application to the Case Western Reserve University (CWRU) dataset

The detection framework is applied to the CWRU rolling element bearing dataset (see [9]), for which a comprehensive description and study can be found in [10]. There are several groups, respectively for Normal and faulty conditions (see Table 1 below – 5 distinct failure modes were extracted for this study).

Condition	Motor Load (HP) Motor speed (RPM)	Number of Kurtograms (level 4)	Phase on the graphics (see Figure 2)
Normal	0, 1 ,2 ,3	119, 236, 236, 237	A (800 images used for training)
Inner Race Fault, ϕ 0.007"		119, 237, 237, 237	B
Inner Race Fault, ϕ 0.0014"	1797, 1772, 1772, 1750, 1730	31, 186,238, 236	C
Inner Race Fault, ϕ 0.0021"		119, 236, 239, 238	D
Ball Fault, ϕ 0.007"		119, 237, 237, 238	E
Outer Race Orthogonal, ϕ 0.007"		60, 236, 237, 237	F

Table 1: CRWU Dataset

The model is first trained on healthy conditions with 800 points from Group A. Then, the framework is applied to detect faulty conditions. The system is considered as faulty when the indicator goes below the threshold 0.4 (see Figure 2 below).

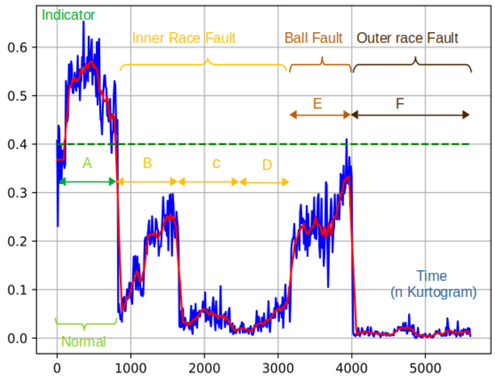

Figure 2: Failure Detection on the CWR Dataset

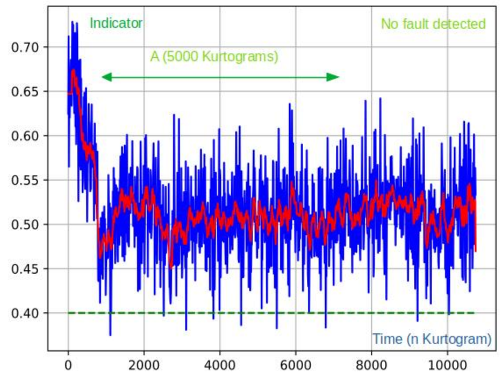

Figure 3: Failure Detection on the IMS Dataset / Channel 1

Analysis and comments (see Figure 2):

- The model is challenging to train as the dataset for normal conditions is small (800 images and 28 images are used to test the generalization capability - or over-fitting risk),
- due to unbalanced data for normal conditions ("load 0" versus two time more for each other loads), low values are observed at the beginning. With a balanced length, the model would have been better trained (for normal conditions, the indicator should be ~ 0.5),
- the dataset is applied to the framework sequentially, whereas in real applications, the transitions are progressive (e.g. from A to B or A to E). However, this study reveals that this model can be easy embedded in real time monitoring to detect precursor signs of failures (which occurs when the indicator goes from 0.5 to a lower value).

Application to the Center for Intelligent Maintenance Systems (IMS) dataset

For a progressive manifestation of failures, the IMS rolling element bearing dataset of the University of Cincinnati is considered, which has been collected on an endurance test rig (see [11] for a description and analysis). The framework is applied on the first test (three several tests are available), for which 34 days of recording accelerometers measures are available, see Table 2 below.

Analysis and comments (see Figures 3, 4 and 5):

- the application of the framework leads to expected theoretical results : no failures for Bearing 1 and failures detected for Bearing 3 and 4 at the end of the endurance test,
- the "health phase" is not homogeneous but the algorithm shows adapative capabilities (the indicators stays around 0.5),
- the learning and detection schemes are easy to implement for a real time-monitoring, and, new updated data can be used to enhance the model.

Dataset description	Channels (1 to 8)	Theoretic Observations [11]	Preprocessing	Results : application of the detection algorithm
➢ 34,5 days Endurance duration ➢ File Recording Interval: ~10min ➢ Accumulated recorded signal: 36 minutes duration : • 2156 Files • 1s at 20 KHz sampling rate • 20480points / file • 8 channels (2 per accelerometer)	Bearing 1 : # 1 & # 2	No damage	➢ Generation of Level 5 – Kurtograms (4096 points) ➢ 5 Kurtograms per file ➢ 10780 Kurtograms for the 2156 file	Channel 1 Training - Fig 3 / Phase A Result : no damage detected
	Bearing 2 : # 3 & # 4	No damage		Not represented
	Bearing 3 : # 5 & # 6	inner race defect		Channel 5 Training - Fig 4 / Phase A Result : fault at day 31
	Bearing 4 : # 7 & # 8	roller element defect		Channel 7 Training - Fig 5 / Phase A Result : fault at day 27

Table 2: IMS Dataset (1st test)

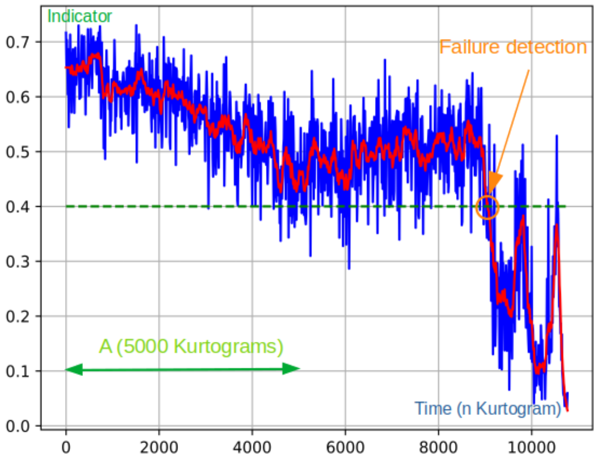

Figure 4: Failure Detection on the IMS Dataset / Channel 5

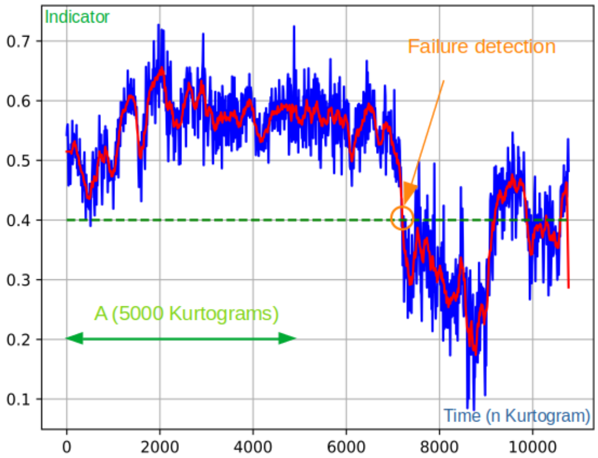

Figure 5: Failure Detection on the IMS Dataset / Channel 7

Application to HUMS23 dataset

Initially, the framework was designed for detecting faults in rolling bearing elements, which causes cyclo-stationary noise when affected by damages on their parts. Any rotating machine or system with a cycle of operating system is subject to similar noise, in particular for gearboxes. As a result, it was decided to apply the methodology to the HUMS2023 Data Challenge [12] to detect as early as possible, the planet gear crack before its propagation causes catastrophic consequences. The results are presented separately on the challenge submission form.

Conclusion

In this article, an innovative framework is proposed, that can be easily embedded in existing systems to monitor in real time rotating machines, avoiding offline, and too late handcrafted signal processing analysis. In this context, an unsupervised deep learning approach is proposed, combined with signal-processing methodologies, to extract relevant and pertinent features for the training phase. Considering that usual operational systems spend most of their time in “up-states” or healthy conditions, eventually under several operating conditions, such as speed or load, obviously more time than in faulty conditions, the framework is adaptative and relies on the intensive use of this generally available dataset in healthy conditions.

The Deep Learning approach is based on the use of Kurtograms to train the model, which can be done online.
As an industrial, IoT Consultants' first goal to provide an online plugin is reached. The efficiency has been tested through the application on two datasets, which leads to the demonstration of a decision tool, which is able to predict in real time precursors of failures, enabling maintenance costs reduction. We are convinced that enhanced results could be obtained by working on alternative unsupervised techniques and signal-processing methods, such as in [13], which could open new research areas applied to the industry.

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