HUMS2023 Challenge Submission

Data Result

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Institutions: IoT Consultants

Publishable: Yes

1. Summary of Findings

IoT Consultants' Health Condition Monitoring Framework was applied to the HUMS2023' challenge Data set to detect as early as possible, the planet gear crack.

The framework is based on an unsupervised deep-learning algorithm combined with signal processing techniques to extract pertinent features of raw accelerometer measures. The first step was to learn a model (one by channel) on data corresponding to healthy conditions. To do so, we considered as an assumption that the first 200 files (out of 526) correspond to "normal conditions", i.e., for which there are no damage.

Once trained (a model is learned for each Channel : IP-1, RF-2, RL-3 and RR-4), the algorithm reveals a point corresponding to an abnormal event, and, from which the health indicator is decreasing. It corresponds to the file nro 332 (out of 526 files) which name is : 'Day025_Hunting_SSA_20220111_101221.mat'.

However, it is worth noting that the machine learning algorithm uses an averaged windows technique to detect such point of interest (initially to reduce false alarms in embedded real time environments). When considering a zoom on the charts, it turns out that the 1st file for which the event can be seen is the file nr 330, corresponding to: Day025_Hunting_SSA_20220111_100623.mat (very close from the Machine Learning's Output).

Conclusion

- earliest convincing detection: **Day025_Hunting_SSA_20220111_100623.mat**
- most accurate trending of fault propagation **:** See figure 5, clear acceleration on **Day026_Hunting_SSA_20220114_124524.mat**

Table 1 Summary of Analysis Results

#	Detection & Trending	Data file name/number	Comments
1	Consistent detection on at least one signal channel; i.e. the fault indicators remain consistently above the threshold.	'Day025_Hunting_SSA_20220111_101221.mat'	See Figures 3.2, 3,3, 3.4
2	Confirmed detection on at least two signal channels; i.e. the fault indicators remain consistently above the threshold.	'Day025_Hunting_SSA_20220111_101221.mat'	See Figures 3.2, 3,3, 3.4
3	Clear multi-channel indication of the characteristic fault features; i.e. faulty planet gear meshing with both the ring and sun gears.	Day025_Hunting_SSA_20220111_100623.mat	See Figures 3.2, 3,3, 3.4 and 4.4 The detection can be made on all channels (best RR-4), except channel 1 for which the change is not so clear (see Figure 3.1). However, there is a min value corresponding to file nr. 332
4	Confirmed trend of fault progression; i.e. a consistent increasing trend started from which file number/name. Day026_Hunting_SSA_20220114_124524.mat	Day026_Hunting_SSA_20220114_124524.mat	Channel RR-3 gives the best trend (Figure 3.4 and zoom represented on figure 5)
5	Confirmed trend of accelerated fault progression; i.e. a consistent exponential increasing trend started from which file number/name	Day026_Hunting_SSA_20220114_124524.mat	See figure 5

2. Analysis Methods

The methodology is presented in our article, submitted for the AIAC20 (see [1]).

The starting point is the target to provide a framework that can be easily embedded in existing systems to monitor in real time rotating machines, avoiding offline, handcrafted signal processing analysis. We propose a deep learning approach, combined with signal-processing methodologies to extract relevant and pertinent features for the training phase.

The innovation relies on an unsupervised approach: there is no need to provide a labeled data set including all faulty scenarios, but only vibration measures, corresponding to healthy states. This is indeed the case for usual operational systems, which spend most of their time in “up-states”, eventually under several operating conditions, such as speed or load.

Damages in rotating assemblies can be detected with the Spectral Kurtosis indicator, but, it remains challenging to select the correct frequency resolution. As a result, Kurtograms are considered (see more details in [1]).

The detection process is based on the changes in the Kurtogram over the time, which reveals new noises generated by begin of cracks in the gearbox. The progression can also be monitored by their evolution.

3. Illustrating Figures

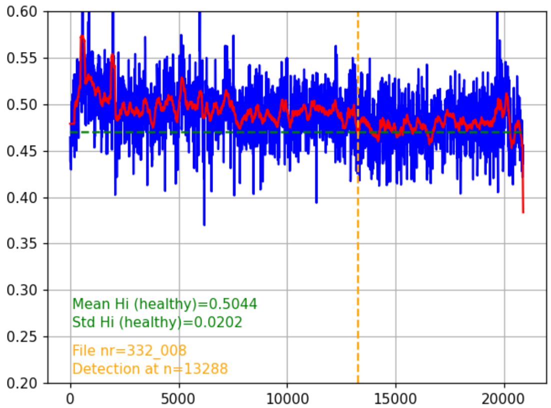

Figure 3.1. Channel IP-1

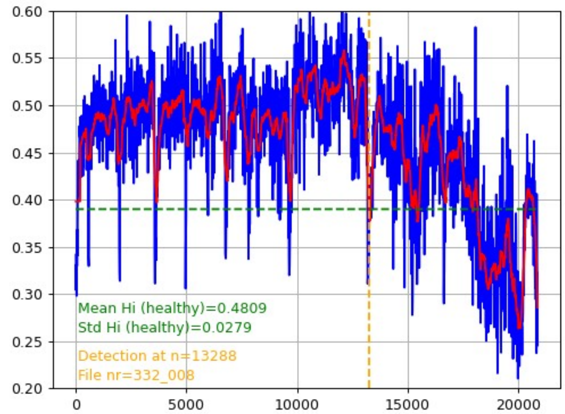

Figure 3.2. Channel RF-2

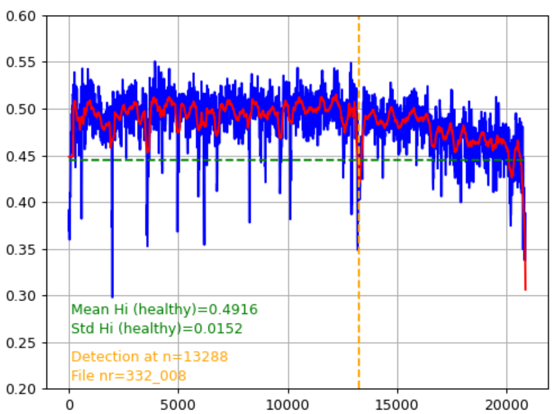

Figure 3.3. Channel RL-3

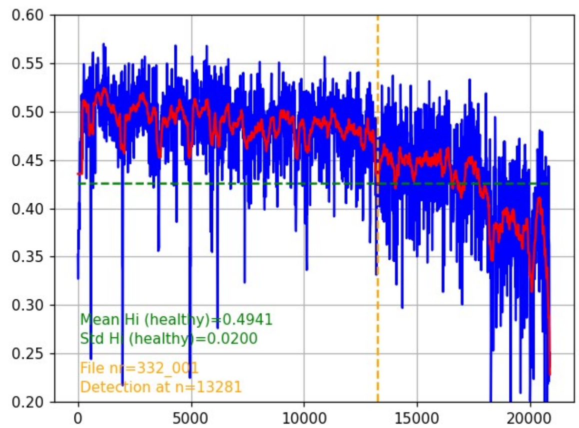

Figure 3.4. Channel RR-4

4. Characteristic Fault Signatures of Early Detection

On the Figures below, for each channel, are represented, from the left to the right :

- the Kurtogram generated by the file Day021_Hunting_SSA_20211208_160102.mat (considered as healthy state)

- the Kurtogram generated by the file Day025_Hunting_SSA_20220111_101221.mat (n-th file detected by the Algorithm as corresponding to a confirmed failure)
- the max kurtosis for the best resolution (given by the kurtograms over a range of kurtograms close to the area of interest ~ 330th file or 13200),

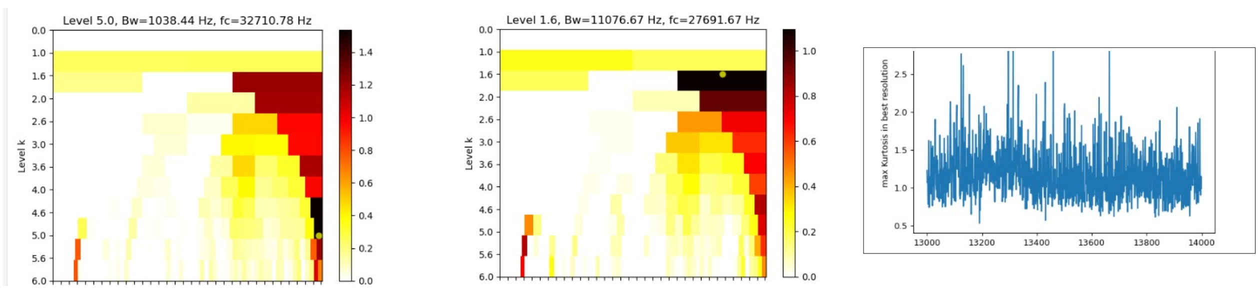

Figure 4.1. Characteristic fault signal of the earliest detection by channel IP-1

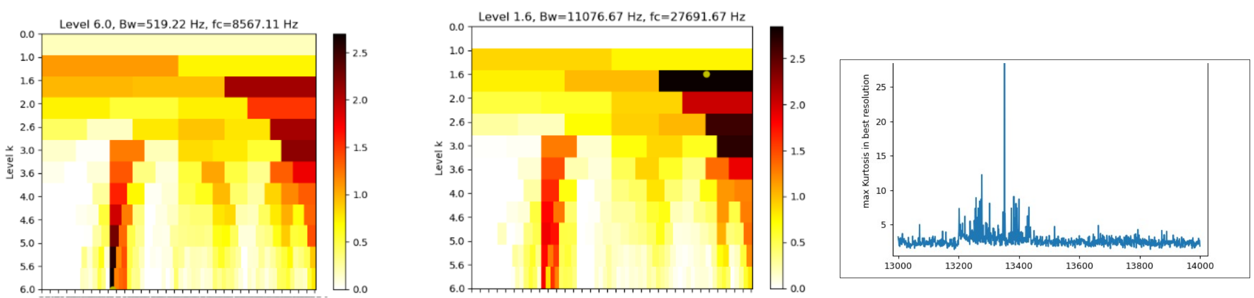

Figure 4.2. Characteristic fault signal of the earliest detection by channel RF-2

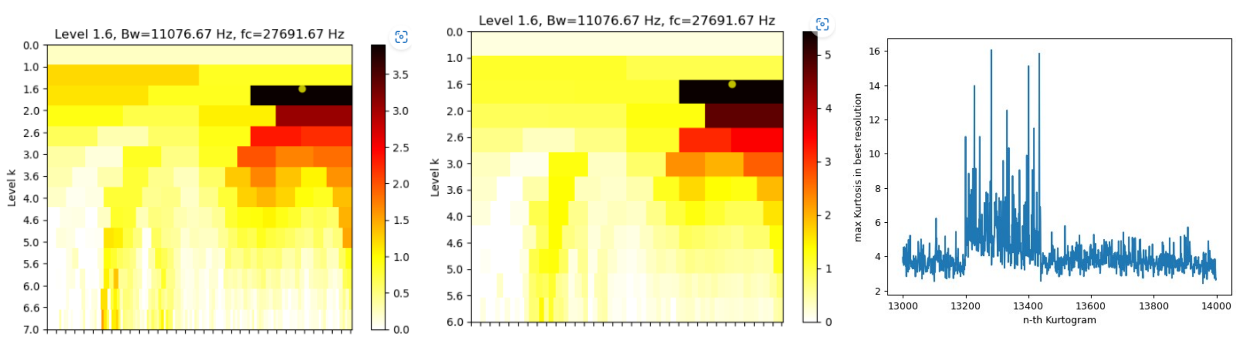

Figure 4.3. Characteristic fault signal of the earliest detection by channel RL-3

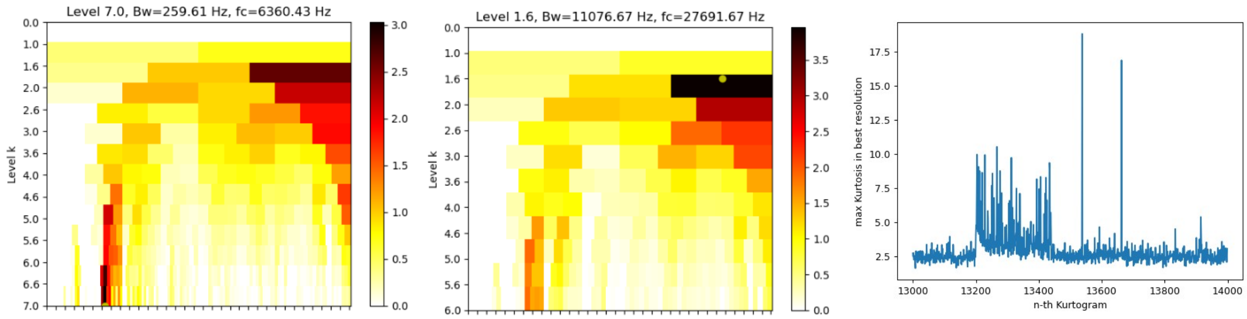

Figure 4.4. Characteristic fault signal of the earliest detection by channel RR-4

Analysis :

- ➢ Figure 4.1 shows no relevant signature detection. The max Kurtosis is slightly similar on both Kurtograms. As a result, IP-1 Channel cannot be efficiently used to detect the failure.
- ➢ Figure 4.2 reveals a change in max Kurtogram (detected by the algorithm) and confirmed by the zoom at point=13200 (corresponding to the 330-th file or Day025_Hunting_SSA_20220111_100623.mat)
- ➢ Figures 4.3 and 4.4 confirm clearly the observation from Figure 4.2.

5.Fault Progression Trending Curve

The following Figure shows the trend of health's indicator (corresponding to the fault propagation) for Channel RR-4 (other channels show not enough relevant progression)

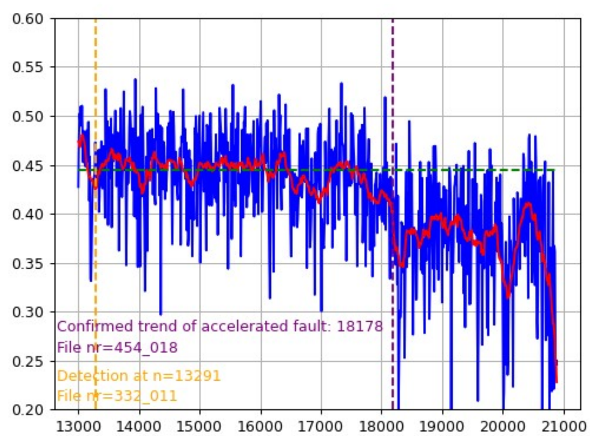

Figure 5. Trending curve for the planet gear fault progression

Analysis:

The figure reveals a point from which there is a clear acceleration : n=18178, corresponding to the file nr 454, or **Day026_Hunting_SSA_20220114_124524.mat**

6. Description of Analysis Methods

Description of fault detection method

The detection is made directly by applying the machine learning algorithm, described in [1] (See Figures 3.1, 3.2, 3.3 and 3.4). However, as the algorithm uses time-averaged windows, it turns out that a zoom (close to the area of interest) reveals an earlier point (See Figure 4.4)

Description of fault trending method

The health indicator provided by the algorithm represents a “pseudo-distance” from healthy conditions (the value 0.5 represents the fact that we are close to “normal”). As a result, this indicator can be considered as a level of damage, going close to 0 when the damages reach a high level. Nonetheless, the framework (the model) was not initially designed to follow the progression: it was designed to alert, in an embedded, real-time environment, once the system leaves its normal conditions (as learned). A useful and interesting extension of the model could lead to address this question, more accurately, through a new research area.

7. Supplement Information

Additional information about the methodology can be found in the article submitted for the 20th AIAC Congress :

[1]: Boussemart, M., Shariat. M, “An industrial unsupervised Machine Learning model combined with a signal processing approach to detect failures in complex rotating assemblies”, AIAC20/HUMS23, Feb 23.