HUMS2023 Result

Data Challenge Submission

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Publishable: Yes

1. Summary of Findings

A fault metric based on the variance of a modified squared-kurtosis (nd_6) of the vibration signal corresponding to a planetary gear tooth has been developed. It is shown that the aggregate of this metric across all 4 channels shows a strong indication of fault emergence.

A definite shift in the fault metric can be seen from file 50 onwards, although an exponential trend is only evident from file 400.

A parallel method based on a subspace distance between the singular spectra of the signal (called Mutual Singular Spectrum Analysis) was also investigated and results reported in an addendum. A deviation from baseline MSSA derived metric shows broad agreement with the nd_6 metric with consistent detection after file 180, although the derived fault metric was quite intermittent. An inter tooth comparison method using MSSA shows some promise although a convincing fault metric could not be derived.

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.	File 045	Deviation of the variance of toothwise kurtosis from baseline across all signals.
2	Confirmed detection on at least two signal channels; i.e. the fault indicators remain consistently above the threshold.		
3	Clear multi-channel indication of the characteristic fault features; i.e. faulty planet gear meshing with both the ring and sun gears.		
4	Confirmed trend of fault progression; i.e. a consistent increasing trend started from which file number/name.	File 045	See Figure 5
5	Confirmed trend of accelerated fault progression; i.e. a consistent exponential increasing trend started from which file number/name	File 420	See Figure 5

2. Analysis Methods

Variance of Tooth-wise Higher Order Statistics

The underlying assumption to this approach is that the vibration signal associated with a tooth meshing event is consistent across teeth apart from the tooth with the fault. Also, the fault is such that the higher order statistics of the vibration signal yield large values.

The data sets are split into segments corresponding to the tooth interaction time. From these subsets of data an ensemble of higher order statistics are evaluated. The variance of these ensembles is evaluated and normalised to the baseline value, (taken as the median of the values from the initial N data sets, in this case N=50.) The higher order statistics considered are: kurtosis and a modified ND_6 statistic [1], each defined as follows:

$$k = \frac{1}{N}\sum_{N}\frac{(x-\bar{x})^4}{\sigma^2} \quad \text{and} \quad \widehat{ND_6} = \frac{1}{N}\sum_{N}\frac{(x-\bar{x})^6}{\sigma^2}$$

Note, that ND_6 differs from the definition given by Tong et-al in that it is normalised to variance squared not variance cubed, making it proportional to signal energy. The variance of the ND_6 , σ_{nd6} was found to be more responsive to the development of the fault than the kurtosis measure.

The fault metric was shown to be sensitive to the changed conditions on gearbox startup each day, so a median filter was applied, in addition the metrics from each channel (Figure 4) were aggregated to obtain a single overall value and the absolute deviation of this from the baseline value is plotted in Figure 5. Note, that although in this case the variance of ND6 over a planet/ring gear interaction was used as the metric, it could be evaluated on the planet/sun interaction period also.

Mutual Singular Spectrum Analysis (MSSA)

The Mutual Singular Spectrum Analysis (MSSA) technique has previously been used in bioacoustics [2] to classify species such as *anuran* (frogs or toads) where their calls often have continuously repeating syllables. Singular Spectrum Analysis (SSA) converts an input signal *X* of length *m* into a matrix of lagged vectors of length *k=m+l-1* where *l* is the lag. The lag was set to 117 samples, equivalent to the tooth interaction time. An autocorrelation matrix (*A*) is calculated, and is of size *lxl.* A subspace representation of the signal is formed by taking eigen-vectors (*U*) of *A* corresponding to the *p* largest eigen-values. Similarity between two signals in this subspace is proportional to the Singular Values of the cross product of U_1 and U_2, where the subspace distance varies between 1 for full correlation to 0 for no correlation between the subspace structures. See [2] for a more detailed overview of the method.

In this case the two signals are from a baseline period (load cycles 17-27) and each load cycle. The number of retained eigen-vectors p=12, which represented >92% contribution by eigen-value from the baseline for all channels. It is proposed that a fault is present when these signals are least similar, indicated by an increase in the subspace distance. See Figure 2.

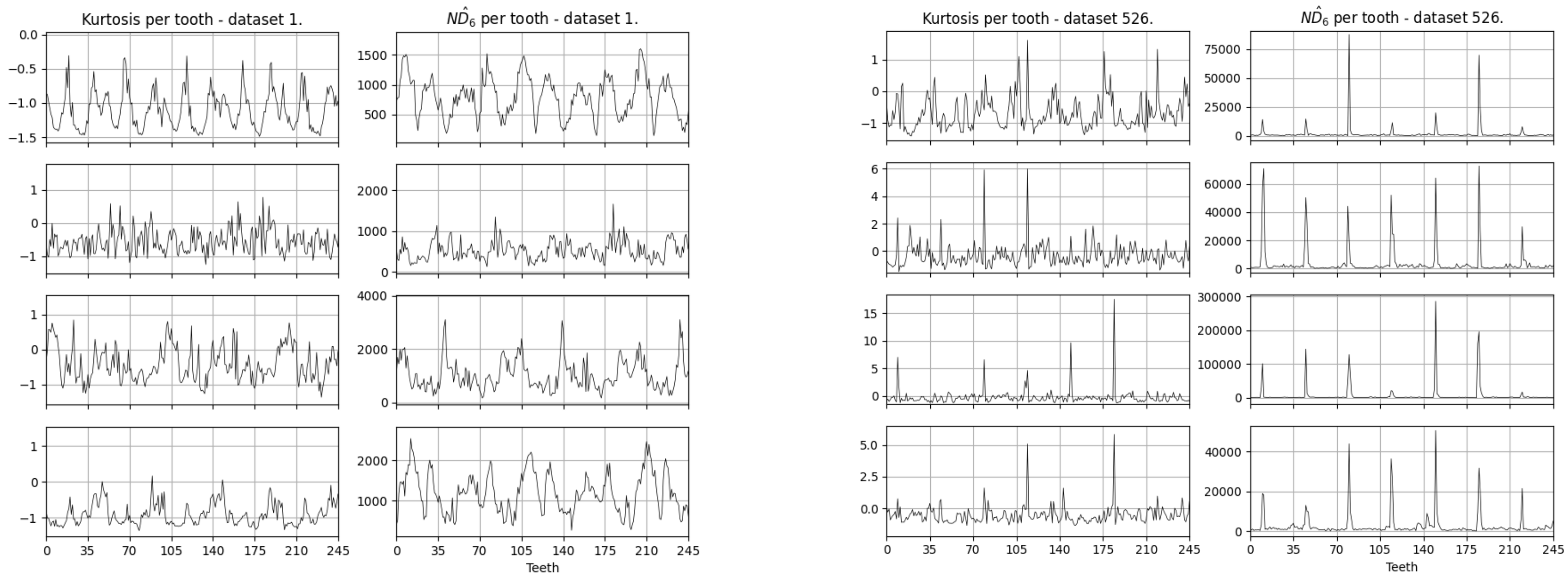

Figure 1 Tooth wise estimates of kurtosis and ND_6 vs tooth number for data set 1 and data set 526. The grid spacing is set at 35 teeth corresponding to a single rotation of the planet gear.. Note the strong peak in the ND_6 indicator.

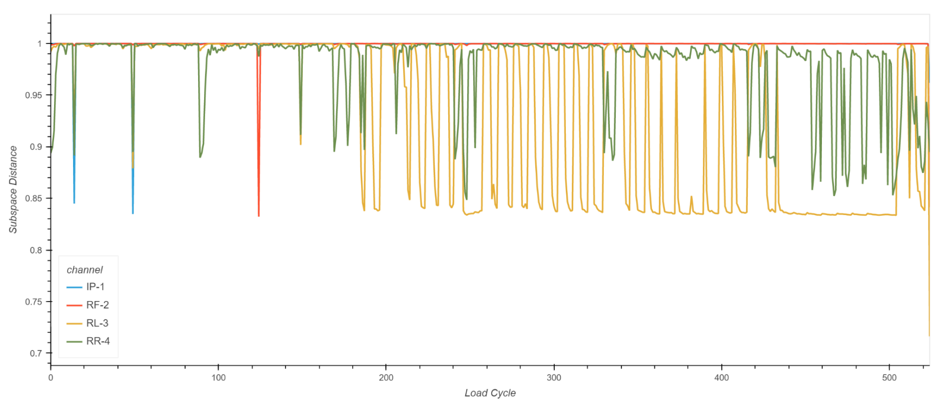

Figure 2: MSSA Sub space similarity between teeth for each channel vs data set. Note reduction in magnitude indicates less similarity.

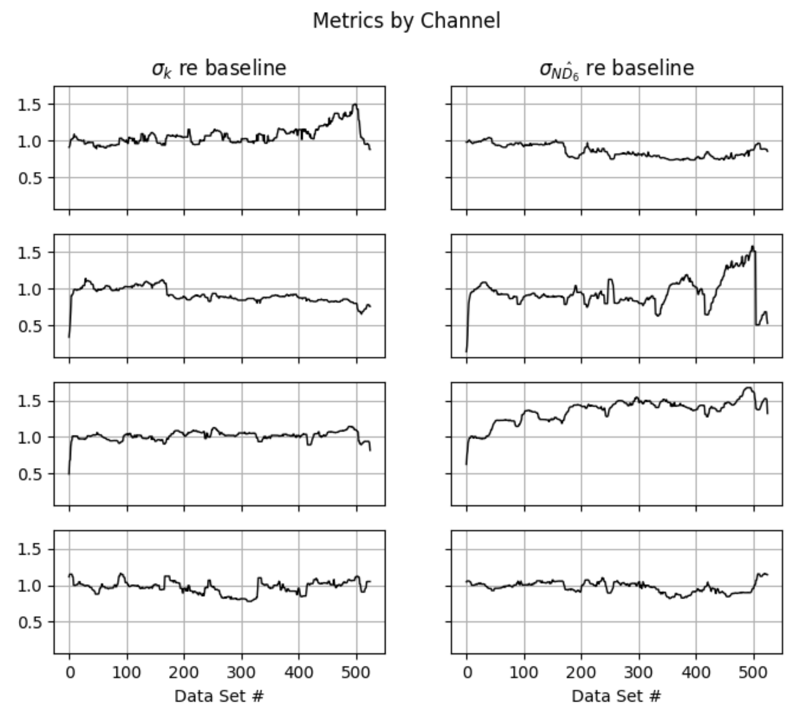

Figure 3: From the above it is clear that no single channel gives a clear early indication of fault severity increasing, but it is evident on some channels that the data is changing.

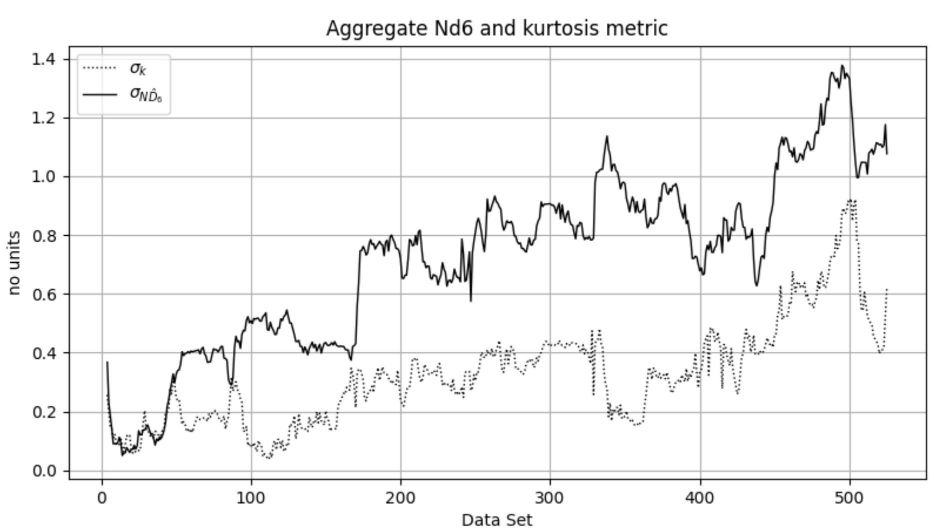

Figure 4: By aggregating across all four channels (shown in Figure 3) the mean square error from the baseline values and stronger indicator is formed.

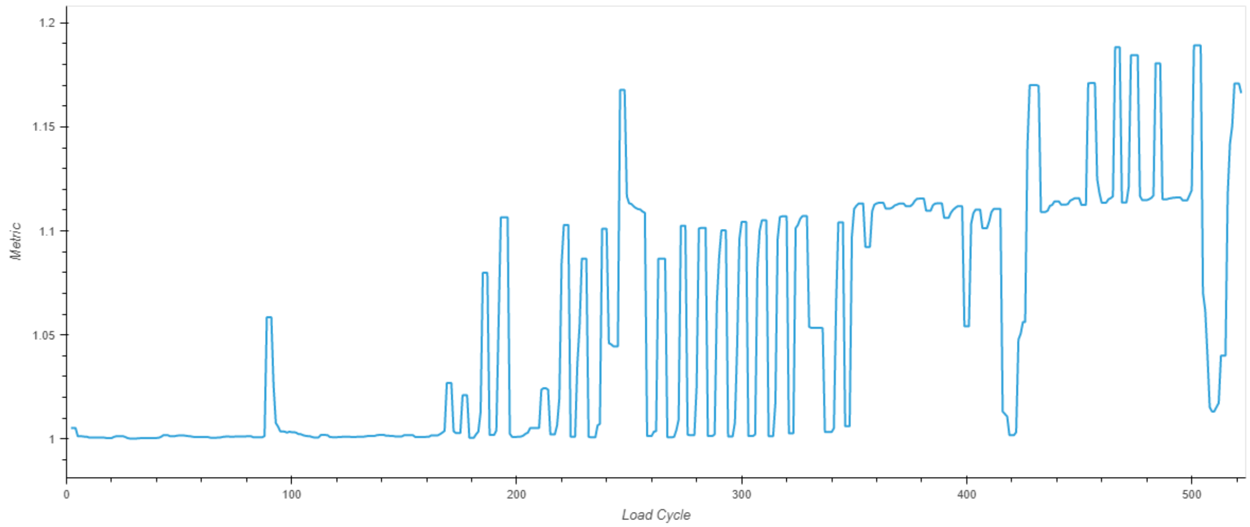

Figure 5: MSSA Fault Indicator vs Data set. Fault indicator defined as Mean Square Error across all channels of subspace distance from baseline, with a rolling 5 channel (see figure 2).

3. References.

[1] "Vibration Separation Methodology Compensated by Time-Varying Transfer Function for Fault Diagnosis of Non-Hunting Tooth Planetary Gearbox", Shuiguang Tong, Junjie Li, Feiyun Cong, Zilong Fu and Zheming Tong, Sensors 2022 22, 557. https://doi.org/10.3390/s22020557.

[2] "Discriminative Singular Spectrum Classifier with Applications on Bioacoustic Signal Recognition", Bernardo B. Gatto, Juan G. Colonna, Eulanda M. dos Santos, Alessandro L. Koerich and Kazuhiro Fukui, https://arxiv.org/abs/2103.10166v1

4. Addendum

Mutual Singular Spectrum Analysis (MSSA)

MSSA is based on a subspace analysis of an autocorrelation matrix, where the signals are represented as linear combinations of basis vectors, ranked by their eigenvalue contributions.
Comparisons can be made between different subspaces by the use of canonical angles, and a simple "distance" metric derived that compares the similarity of signals based on their structure only.

Method

Singular Spectrum Analysis (SSA) converts an input signal *X* of length *m* into a matrix of lagged vectors of length *k=m+l-1* where *l* is the lag. This matrix consisting of a series of delayed embedded vectors is called the trajectory matrix, *H* and has a Hankel structure. In many applications the delay is a time delay, however in this application the delay represents an angular delay. The length of the embedding was chosen to be *l=117*, which represents the angle subtended by a single tooth. The autocorrelation matrix *A* can be calculated from the Hankel matrix *H*, and is of size *lxl.*

$$A = HH^\top$$

An Eigenvalue decomposition of the autocorrelation matrix can be calculated,

$$A = U \Sigma U^\top$$

Where U is a matrix of basis vectors ϕ_k and Σ are the Eigenvalues in descending order.

A truncated subspace that represents the signal can be constructed by retaining the eigenvectors representing the p largest Eigenvalues. Similarly a noise subspace can be constructed from the remaining Eigenvectors.

Given a signal of any length, a lag l and a subspace length $p < l$ a compact representation $\overline{U}$ of the signal can be created. To measure the similarity between two different signals represented by subspaces $\overline{U}_1$ and $\overline{U}_2$ the Singular Value Decomposition of the matrix $p \times p$ matrix W

$$W = \overline{U}_1^\top \overline{U}_2$$

with singular values δ has canonical angles $\Theta_i = \arccos(\delta_i)$. Similarity between the two subspaces is proportional to this angle. The subspace distance varies from 1 to 0 as the uncorrelated structures increase.

Baselines

MSSA:

For each load cycle, $\overline{U}$ was calculated for each channel of (99 x 36 x 117 data points). The number of retained Eigenvectors was fixed at p=12, which gives a compact representation of the signal of dimension 117 x 12.

A baseline subspace (also of fixed *p=12)* was calculated for each channel from a dataset consisting of 10 load cycles concatenated together by channel (so 10 x 99 x 36 x 117 data points). The start of the baseline was offset by 17 load cycles to ignore any influence of cold operating temperatures at the start of the day.

Kurtosis / ND_6:

The baseline was taken as the median value over the first 50 data sets of the sum of the squares of variance of the per tooth kurtosis or ND_6 of each channel.