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Detecting planet gear crack propagation using FRESH filters

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Abstract

Condition monitoring of planetary gears is crucial as they are employed extensively and often in safety critical applications. One crucial failure mode in planetary gears is fatigue cracking, where a crack is initiated in the outer race of the planet bearing and then propagates through the gear. Detecting these fatigue cracks was the goal of the HUMS 2023 data challenge. In order to tackle this issue of fatigue crack detection, the use of Frequency-Shift (FRESH) filters is proposed in this work. The proposed FRESH filters aim to extract cyclostationary components in specific cycle frequencies. When considering a previously proposed pipeline based on time synchronous averaging and Hilbert based demodulation techniques, the addition of a FRESH filtering step to extract the cyclostationary components specific to the planet gear allows for significantly earlier detection. And thus, also for planet gear crack detection, FRESH filters are shown to be an effective methodology for fault detection.

Keywords: Crack detection, condition monitoring, FRESH filtering.

Introduction

Reliable operation of planetary gearboxes is crucial in various safety-critical applications such as helicopters [1]. In order to ensure safe operation of these gearboxes vibration based condition monitoring techniques have been developed which aim to detect faults at an early stage and monitor the progression of the fault [2]. In order to detect the signature of the fault in these vibration signals several signal processing and machine learning techniques have been proposed [3], [4].

In an effort to benchmark the different approaches of analysing the vibration signal with the goal of planet gear fatigue cracking, the Defense Science and Technology Group (DSTG) of the Department of Defense of the Australian Government prepared a dataset which was the basis of the 13th International Conference on Health and Usage Monitoring (HUMS 2023) data challenge [5]. The participants of this data challenge were tasked with the development of an indicator which could detect the induced fatigue crack fault as soon as possible and monitor the fault with a clear trending indicator.

Frequency Shifted (FRESH) filters have shown great promise in extracting cyclostationary components from vibration signals and have been used successfully for fault detection in bearings [6]. Therefore, in this work the use of FRESH filters for gear crack monitoring is explored.

The remainder of this work is as follows. The next section discussed the working principle of the FRESH filters and how the filter weights are determined. Next the dataset is discussed more in depth which is followed by a section outlining the proposed data processing pipeline. Afterwards, the results are presented followed by the conclusion.

FRESH filters for extraction of cyclostationary signals in vibration monitoring

FRESH filters are equivalent to a polyperiodic time-variant filter with an input-output relation of:

$$y(t) = \sum_{m=1}^{M} h_m(t) \otimes x_{\alpha_m}(t) \tag{1}$$

where $x_{\alpha_m}(t) = x(t)\exp(j2\pi\alpha_m t)$ with a set of cycle frequencies $\{\alpha_m\}$. Based on the theory of cyclostationarity, Gardner derived the optimal filter weights of the FRESH filter which minimizes the time-averaged squared error between a target signal $d(t)$ and the filter output $\{\alpha_m\}$. The solution of the time-averaged square error problem is then given by the equation [7]:

$$\sum_{m=1}^{M} S_x^{\alpha_k-\alpha_m}\left(f - \frac{\alpha_m+\alpha_k}{2}\right) H_m(f) = S_{dx}^{\alpha_k}\left(f-\frac{\alpha_k}{2}\right), k = 1,2,\dots,M \tag{2}$$

where S_x^{α} is the spectral correlation density, S_{dx}^{α} the spectral cross correlation density and $H_m(f)$ the impulse Fourier transform of the impulse response $h_m(t)$. This solution is often called the optimum FRESH filter. It should be noted that in literature the term cyclic Wiener filter is sometimes used. However, the optimum FRESH filter can only be a cyclic Wiener filter when $\{\alpha_m\}$ is chosen optimally [7]. In the case of vibration signals this cannot be guaranteed. When $\{\alpha_m\}$ is not chosen optimally the resulting filter weights according to Eq. (2) are a constrained optimum to the general time-averaged square error problem and thus the terminology of optimum FRESH filters will be used.

When the assumption is made that the measured signal $x(t)$ compromises of the target signal $d(t)$ with an additive noise signal $n(t)$ which is uncorrelated to $d(t)$ and where $S_n^{\alpha} = 0$ for the considered cyclic frequencies $\{\alpha_m\}$, then the input measured signal $x(t)$ can be used as the target signal when extracting the cyclostationary components. Note that $S_n^{\alpha} = 0$ will never hold for the zero cyclic frequency case and thus the zero cyclic frequency will be left out of the considered cyclic frequencies [6].

Fatigue crack propagation dataset

The considered dataset was used in the HUMS 2023 data challenge; the dataset consists of vibration measurements gathered by DSTG on a Bell Kiowa 206B-1 (OH-58) main rotor gearbox with four planets and contains measurements of four sensors located on different positions on the gearbox. The gearbox was seeded with a fault by creating a notch in the planet gear and was then subjected to a series of load cycles in order to propagate a fatigue crack through the gear.

The dataset compromises of hunting tooth averaged measurements of four sensors positioned on the outer casing. Three sensors were located on the ring near the planetary stage and one near the pinion-bevel stage. The sensors were sampled at 66409.16 Hz and the gearbox was operated with an input speed setpoint of 100Hz which resulted in a planet carrier rotation of 5.7Hz, a planet rotational speed of 16.2Hz and a planetary stage gear mesh frequency of 567.6Hz.

The original dataset, as used in the HUMS 2023 contained 526 measurements spanning 60 load cycles. Later an additional dataset was shared containing 282 measurements of the remaining 34 load cycles after the creation of the notch that initiated a gear crack fault.

Following [8], the signal is also preprocessed by subtracting the planet carrier time synchronous average in order to remove the periodic components due to the planet location with respect to the sensor position.

Application of FRESH filters in fatigue crack detection

The FRESH filters applied are optimized according to Equation 2 with the target signal equal to the input signal. The considered cycle frequencies are the first 6 harmonics of the planet rotational speed and their negative components. A filter length of 1024 points is chosen and the spectral correlation densities are estimated using the frequency smoothing method [9].

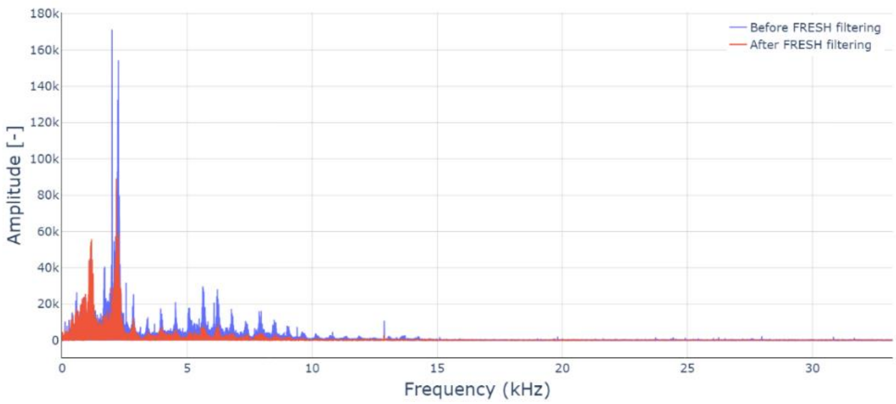

Figure 1: Frequency representation of a signal with a severely progressed fault (file 522 of the original dataset). Sensor located on the rear of the ring gear.

In this work, the FRESH filters are used as a automated frequency selection tool before computing the square envelope spectrum (SES). Figure 1 compares the signal before and after applying the optimum FRESH filter on a signal with a well-developed fault developed fault (file 522 of the original dataset) where it is clear that the FRESH filter selects the frequency bands related to twice and four times the gear mesh frequency of the planet. The higher order harmonics of the gear mesh frequency are also still visible after applying the FRESH filters but frequencies higher than 10kHz are greatly reduced in amplitude. Thus, the FRESH filters seem to focus on the frequencies related with the gear meshing.

After the FRESH filtering step the square envelope is extracted and summed over the three sensors on the planetary stage. Next, the Discrete Time Fourier Transform (DFT) is taken in order to represent the signals in the SES domain. In the SES domain, the absolute values of several peaks related to the fault are summed together in order to obtain a single indicator. The peaks summed are the first ten harmonics related to the planet rotational speed.

The final indicator is then smoothed with a median filter of 20 files [3]. The threshold to determine the fault detection point is set based on the median plus three times the median absolute deviation around the median of a healthy reference which is taken to be of the first 100 files of the dataset.

Results

The results of applying the FRESH filtering approach on the original dataset can be seen in Figure 2a, where the first detection point is at file 127 which is much earlier than applying the methodology without the FRESH filtering step which detects the fault at file 145. This is significantly earlier than the previously best reported results which report file 175 as the earliest detection [3].

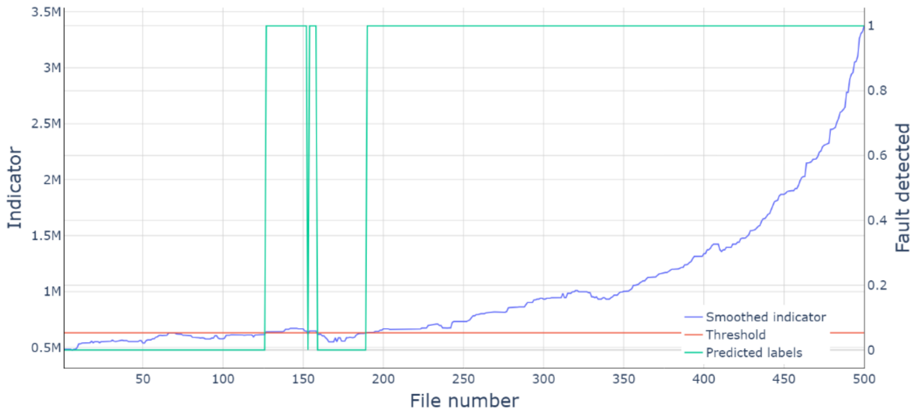

Figure 2: The proposed indicator and threshold using FRESH filters on the original dataset up to file 500. Final files not plotted due to large exponential increase.

However, it should be noted that the indicator drops back down the threshold between file 159 and 189, which also happens for the indicator without FRESH filtering between file 162 and 178. The likely cause is the effect of the temperature of the gearbox and oil temperature on the indicator value. This is clear when looking at Figure 3 where the indicator value averaged per load cycle and the temperature measured at the outlet of the gearbox is shown. There is a clear drop in the indicator values when the temperature drops. The temperature dropping at load cycle 55 due to nightly shutdown is likely the cause of the indicator dropping back below the threshold around these files.

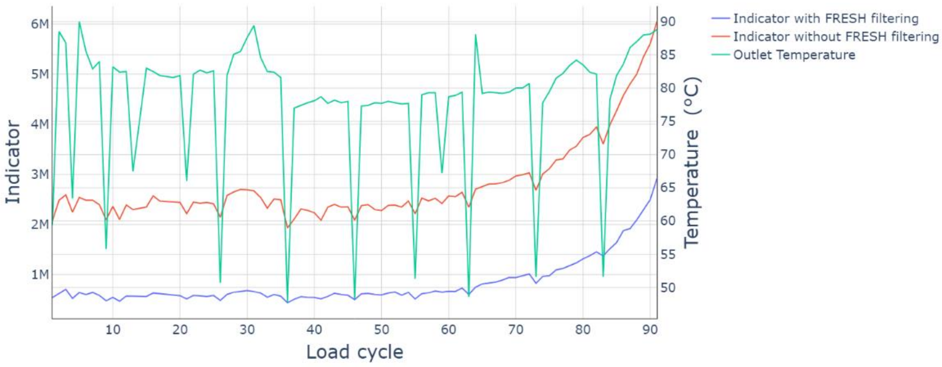

Figure 3: The proposed indicators averaged per load cycle and outlet temperature over the full dataset. Last load cycles not shown due to exponential increase.

The result of applying the indicator on the full dataset (original challenge dataset and additional dataset) is shown in Figure 4. Applying the indicator on the full dataset results in an increase above the threshold early at file -54 before dropping down again (using the naming convention of [3] where the zero file is the first file of the original dataset). This is once again due to the increase in temperature at cycle 30 and 31.

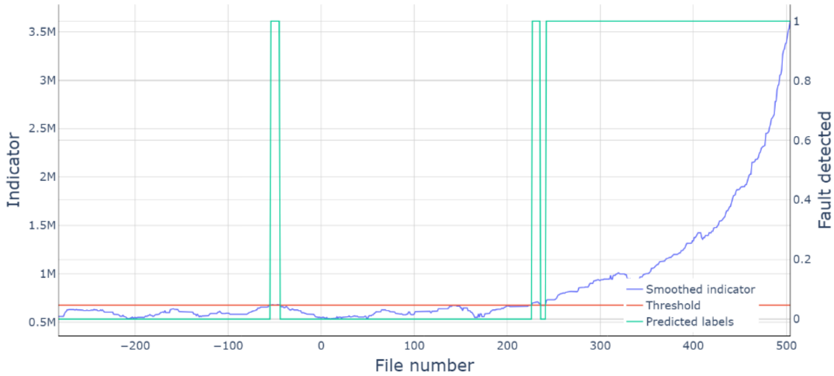

Figure 4: The proposed indicator and threshold using FRESH filters on the full dataset up to file 500 of the original dataset. Final files not plotted due to large exponential increase.

In order to verify which indicator is most sensitive to the temperature effects, the trend of the indicators is quantified. As the crack is only increasing in size the indicator value is expected to only go up. The more the indicator would be affected due to the varying temperature, the worse the trend is expected to be. In order to quantify the trend the Spearman rank correlation coefficient is used [10]. The coefficient is used to verify if there is a monotonic relation between the load cycle and the average indicator value of the load cycle where a value of 1.0 indicates a perfect monotonous relation and a value of zero indicates no relation.

Table 1: Spearman rank correlation coefficient of the indicators with and without filtering

	Original dataset	Full dataset
Indicator without FRESH filtering	0.967	0.716
Indicator with FRESH filtering	0.972	0.801

As can be seen in Table 1, the proposed indicator using FRESH filters has a higher Spearman rank correlation coefficient on both the original dataset and the full dataset. This indicates that the inclusion of the FRESH filters resulted in a better trending indicator. It should be noted that both the indicator with and without FRESH filters has a much lower correlation coefficient on the full dataset than the original dataset. This can be attributed to two factors: the smaller fault size and the less tight temperature control of the first cycles. First, the smaller fault size results in a less severe fault signature which can be easier overpowered by external influences. Moreover, the first load cycles had a less tight temperature and torque control, which also resulted in the same effect of indicators rising and falling below the threshold in previous studies [3].

Conclusion

This work presents the application of FRESH filters for the monitoring of gear cracking in planetary gearboxes. The FRESH filters are shown to be able to extract the relevant frequencies for fault monitoring resulting in earlier fault detection and a better trend on the HUMS 2023 data challenge dataset. Interestingly, the frequencies which are selected by the FRESH filtering are related to the gear meshing frequencies of the planetary gearbox.

Furthermore, the effect of gearbox temperature on the indicators is explored showing that both the indicators with FRESH filtering and without are affected by gearbox temperature. Further work is required to develop indicators that are as little as possible effected by these temperature changes and to further understand the effect of temperature on gear cracking fault signatures.

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