Tracking Bearing Degradation using Gaussian Wavelets

Tony Galati[1]

[1] *Aerospace Division, Defence Science and Technology Group,*
506 Lorimer Street, Fishermans Bend, Victoria, 3207, Australia

Abstract

This paper investigates the use of Gaussian wavelets for tracking the degradation of rolling element bearings. Spalls in bearing raceways or rolling elements lead to impacts which excite structural resonances. Gaussian wavelets are shown to correlate well with these structural resonances when they appear in the measured vibration signal. Impacts are deemed to be detected in the vibration signal whenever the correlation with the Gaussian wavelet exceeds a predetermined level. As the spalled area increases in the bearing over time, the corresponding rate of impacts increases. Bearing degradation is tracked through monitoring the impact rate measured using the Gaussian wavelet. The technique is validated on vibration data obtained from a naturally occurring fault in the epicyclic planet gear bearing in a helicopter main rotor gearbox.

Keywords: Bearing Fault, Gaussian Wavelet, Prognosis.

Introduction

Many vibration analysis techniques for rolling element bearing health monitoring have been developed to date. A recent overview [1] shows that the focus has been primarily on detection and diagnosis. A diagnosis informs you that a bearing is faulty, but does not provide information about how rapidly the bearing is deteriorating, or what its remaining useful life is. These are important considerations when developing or implementing maintenance policy.

When a rolling element passes over a localised raceway spall, or a spall on a rolling element passes into the contact zone, the corresponding impulse response excites structural resonances. These structural resonances are localised not only in frequency, but also in time, due to structural damping. Wavelets are also localised in both frequency and time, and it is this property which has been used successfully for bearing fault diagnosis [1, 2].

The approach developed in this paper is intended to be applied after diagnosis of a fault, and focuses on tracking bearing degradation over time. In essence, the approach uses an optimal wavelet to mimic the bearing fault impulse response in the measured vibration signal. A wavelet is deemed optimal if it is well correlated with the bearing fault impulse response in the vibration signal. As the number of spalls increase over time (i.e. as the bearing degrades), the rate of impulse generation, and consequently the wavelet correlation rate, also increase over time. Thus, monitoring the correlation rate provides a means of monitoring the degradation of the bearing.

The idea described above is dependent on a good correlation between the wavelet and the impulse response to the bearing fault in the measured vibration signal. For this reason, Gaussian wavelets are chosen because of their general similarity to transient structural vibrations [3]. However, the wavelets still need to be optimised (or tuned) to the specific structural response of the mechanical system of interest.

Procedure for Tracking Bearing Degradation

The procedure for tracking bearing fault degradation can be divided into two main steps. The first step is to find the optimal Gaussian wavelet that produces a good correlation with the bearing fault impulse response in the measured vibration signal. A conditional optimisation using the Continuous Wavelet Transform (CWT) is used to find the optimal Gaussian wavelet parameters. To facilitate this, Gaussian wavelets are introduced first before details of the optimisation procedure are presented.

The second step, Degradation Monitoring, involves using the optimal Gaussian wavelet parameters found in the first step to monitor the degradation of the bearing over time. A single-scale CWT, using the optimal Gaussian wavelet parameters, is used to identify the bearing fault impulse responses in the measured vibration signal. A cumulative count of the number of correlations is extracted from the single-scale CWT by first zeroing all points of the CWT which fall below a pre-set threshold, and then integrating this modified CWT over time. The cumulative correlation count can then be used as an indicator of the cumulative degradation of the bearing over time, and its derivative to estimate the rate of degradation.

Gaussian Wavelets

The family of Gaussian wavelets are derived from the exponential (Gaussian) function, $G^{(0)}(t) = \exp(-t^2)$, where $t \in (-\infty, \infty)$. For $n = 1, 2, \ldots$, we define the *n*th Gaussian wavelet, $G^{(n)}(t)$, to be the normalised *n*th derivative of the Gaussian function $G^{(0)}(t)$, that is:

$$G^{(n)}(t) = \alpha_n \frac{d^n}{dt^n} G^{(0)}(t), \tag{1}$$

where α_n is a normalisation coefficient. Some examples of Gaussian wavelets are shown in Fig. 1.

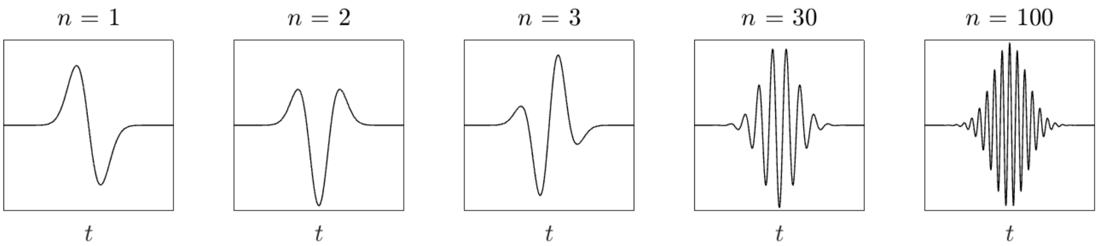

Fig. 1: Gaussian wavelet examples for orders n=1, 2, 3, 30 and 100

Finding the Optimal Gaussian Wavelet

The CWT is used to find the Gaussian wavelet which best simulates the impulse response of the bearing fault. Let $y(t)$ denote the vibration signal, then the CWT of $y(t)$ using a Gaussian wavelet of order n is given by:

$$W(n,s,t) = \int_{-\infty}^{\infty} y(\tau) G^{(n)}\left(\frac{\tau - t}{s}\right) d\tau \, , \tag{2}$$

where s is referred to as the scale parameter. Note that whilst s can be any real number, for this application sufficient fidelity is achieved through considering only positive integer values for s, i.e. $s = 1, 2, \ldots$.

For digital applications, the vibration signal and Gaussian wavelet are sampled at discrete time points only. Consequently, to avoid aliasing when applying Eqn. 2, the scale, s, must be sufficiently large for the wavelet order n. Conversely, for each scale s there is a maximum wavelet order n. To facilitate this, an empirical relationship was derived which provides an upper bound for n as a function of s:

$$2n \le \pi^2 (s-1)^2 - 1 \, . \tag{3}$$

Finding the optimal wavelet parameters is formulated as a constrained optimisation problem in terms of the CWT of the bearing vibration signal:

$$(\hat{n}, \hat{s}) = \arg\max_{n,s} E(n,s), \tag{4}$$

$$E(n,s) = \frac{1}{s^2} \int_{-\infty}^{\infty} \| W(n,s,t) \|^2 \, dt \tag{5}$$

where $\hat{n}$ and $\hat{s}$ are the optimal wavelet order and scale respectively. When performing the optimisation in Eqn. (4), the following two constraints are employed:

(C1) The wavelet parameters, n and s, are constrained to satisfy Eqn. 3.
(C2) The maximum should be taken from a proper "turning point" of $E(n,s)$.

The first constraint is necessary to avoid aliasing. $E(n,s)$ is said to reach a proper "turning point" at the specific point (n,s) if (i) $E(n,s) > E(n-1,s)$ and (ii) $E(n,s) > E(n+1,s)$. In some cases, the inequality in (ii) cannot be assessed because the specific pair $(n+1,s)$ does not satisfy the constraint in Eqn. 3. This is further illustrated in Fig. 3 in the section "Finding the Optimal Gaussian Wavelet Parameters" below.

In order for the solution of Eqn. 4 to be well correlated with the bearing fault impulse response, the signal to noise ratio of the impulse response must be reasonably high; i.e. the impulse response must not be masked by other signal components. For all but the simplest applications, this implies that $y(t)$ be appropriately filtered to separate the bearing impulse response from the other signal components such as the gear meshing vibration and other unrelated spectral content.

Bearing Degradation Monitoring

The optimal wavelet parameters, $\hat{n}$ and $\hat{s}$, determine a unique Gaussian wavelet which best correlates with the bearing fault impulse response. At each point in time that a bearing fault impulse is generated, a corresponding peak will occur in the single-scale CWT, $W(\hat{n},\hat{s},t)$.

The method proposed here is to obtain an estimate of the cumulative "count" of the peaks in $W(\hat{n},\hat{s},t)$ through the integration of a modified form of the single-scale CWT, $W(\hat{n},\hat{s},t)$. The modified form of the single-scale CWT, denoted $w(\hat{n},\hat{s},t)$, is obtained by filtering out the background noise using a pre-determined threshold level, w_0. That is, let $w(\hat{n},\hat{s},t) = W(\hat{n},\hat{s},t)$ for all *t* such that $\|W(\hat{n},\hat{s},t)\| > w_0$ and $w(\hat{n},\hat{s},t) = 0$ otherwise. Then, the following measure is proportional to the cumulative correlation peak count:

$$C(t) = \frac{1}{\hat{s}^2}\int_0^t \|w(\hat{n},\hat{s},\tau)\|^2 \, d\tau \,, \qquad (6)$$

and its derivative with respect to time, $\dot{C}(t)$, will be approximately proportional to the bearing fault impulse response rate, and thus to the rate of degradation of the bearing at time *t*.

Bearing Fault Application

Bearing Fault Test

A Bell 206 helicopter main rotor gearbox was tested in DST Group's Helicopter Transmission Test Facility (HTTF) as part of the research program into developing condition monitoring, diagnostic, and prognostic capability for helicopter transmission systems. The Bell 206 main rotor gearbox is shown in Fig. 2.

The test, which ran for approximately 160 hours, succeeded in initiating and growing a naturally occurring fault on the planet gear spherical-roller bearing. Spalling damage occurred mostly on the inner races as shown in Fig. 2, with some of the rolling elements also damaged (not shown). The photos in Fig. 2 were taken at the end of the test. There was very little damage to the outer race, which is integral with the planet gear.

During the test, vibration data were recorded from accelerometers fitted to the gearbox housing in a number of different locations. Shaft rotations were tracked using tachometers fitted to both the input and output shafts of the gearbox. Wear debris were monitored in real time using a MetalSCAN[1] debris monitoring system fitted into the oil scavenge line upstream of the oil filter.

[1] An oil debris monitoring system produced by GasTOPS, http://www.gastops.com/metalscan.php.

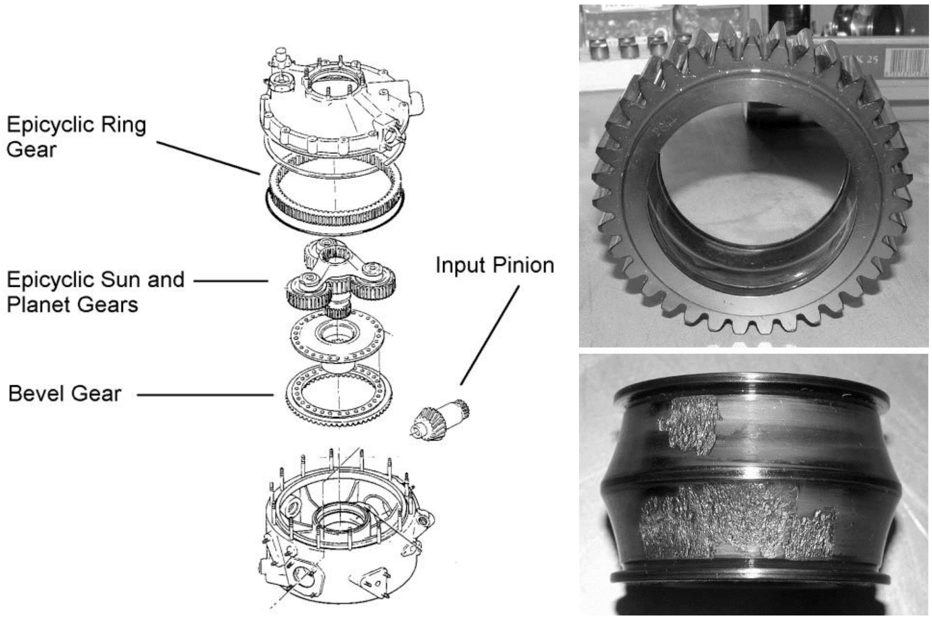

Fig. 2: Bell 206 main gearbox (left), planet gear and planet bearing (right)

Bearing Signal Isolation

Finding the optimal Gaussian wavelet requires a good signal to noise ratio for the bearing fault signal. The raw vibration signals recorded during the test are dominated by the complex harmonic series from the input pinon/bevel gear meshing, and the epicyclic gear meshing. Signal components related to the bearing fault are much lower in amplitude. The bearing fault signal must therefore be separated from these dominant spectral components before the wavelet method can be employed.

Separation of the bearing fault signal was previously achieved by Dr N. Sawalhi, as described in Ref. 4, in which he also correctly diagnosed the planet bearing fault.[2] The technique he used for separating the bearing fault signal from the gear meshing and other dominant spectral content was a combination of Discrete-Random Separation (DRS) and band-pass filtering. The same technique is applied for this analysis.

Finding the Optimal Gaussian Wavelet Parameters

The optimal Gaussian wavelet parameters are obtained using the DRS and band-pass filtered vibration signal, when the fault is in its incipient just-detectable stage, which occurs 80 hours into the test. A plot of $E(n,s)$ for two values of scale s is shown in Fig. 3 (left plot). Each $E(n,s)$ plot terminates at the maximum value of n determined by the constraint in Eqn. 3. The right side plot in Fig. 3 is a colour-map of $E(n,s)$ over a range of (integer) scales and wavelet orders. The amplitude of $E(n,s)$ is displayed on the map using a reverse grey-scale from 0 to 5, with amplitude increasing as the colour darkens.

[2] The analysis was performed blindly, i.e. Dr Sawalhi did not know what type of fault was present in the gearbox during his analysis.

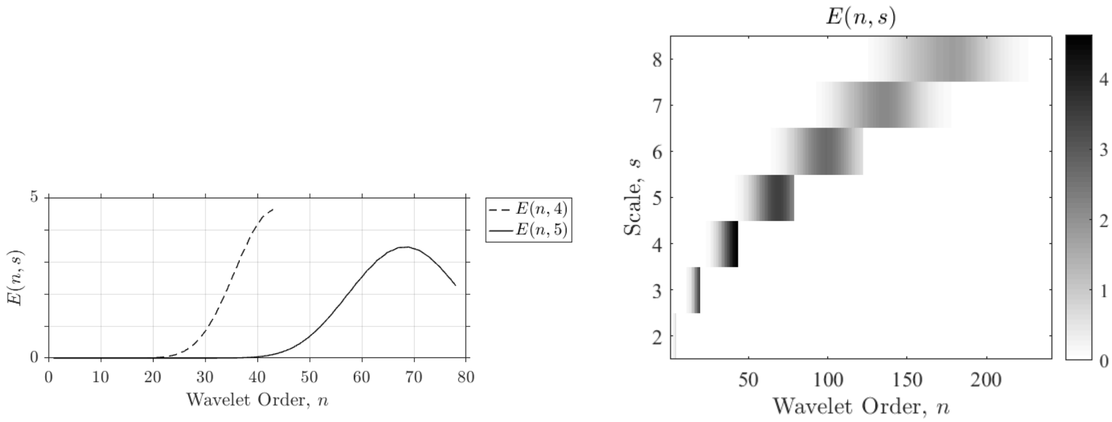

Fig. 3: Left: $E(n,4)$ and $E(n,5)$. *Right:* $E(n,s)$ *order-scale colour-map*

The plot of $E(n,4)$ illustrates how the constraint in Eqn. 3 can lead to a local maximum that is not a turning point. A similar result occurs for $s < 4$, although these results are not as obvious in the colour-map plot.

For $E(n,5)$, a proper turning point and local maximum occurs at $n = 69$. In the colour-map plot it is clear that proper turning points (and corresponding local maxima) are obtained for $s \geq 5$; however, the global maximum (at proper turning points) occurs at $s = 5$. Hence the optimal Gaussian wavelet parameters are, $\hat{n} = 69$ and $\hat{s} = 5$.

Tracking the Degradation of the Planet Gear Bearing

The optimal Gaussian wavelet, with parameters $\hat{n} = 69$ and $\hat{s} = 5$, was applied to the DRS and band-pass filtered planet bearing fault data. Due to the limited number of data sets available with the bearing in a healthy state, the threshold level, w_0, was set using a multiple of the maximum value of the CWT on the first available data file: $w_0 = 1.05 \times \max \left\| W(\hat{n}, \hat{s}, t) \right\|$. The value of the multiplier, 1.05, was not found to be significant, with the technique working well for values up to 1.4.

A plot of $C(t)$ covering the duration of the test is shown in Fig. 4 (left). For comparison, the cumulative mass of wear debris obtained from the MetalSCAN sensor is plotted in Fig. 4 (right).

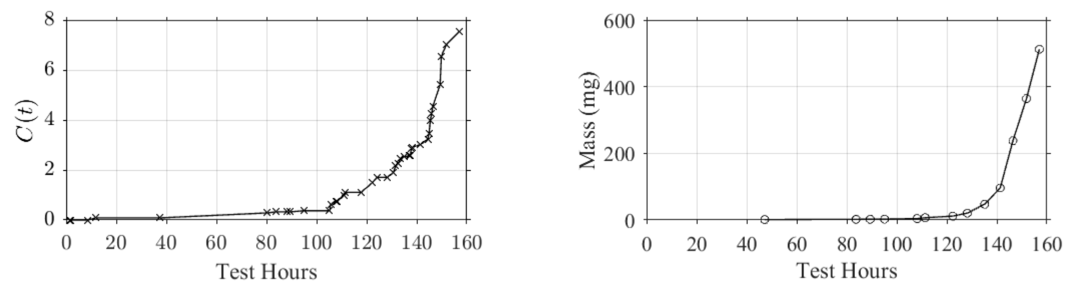

Fig. 4: Left: Gaussian wavelet correlation method. Right: Cumulative mass of wear debris

The wear debris data can reasonably be expected to provide a good measure of the cumulative degradation of the bearing over time. A comparison of the two plots in Fig. 4 indicates that $C(t)$ has a very similar trend to the cumulative mass of wear debris; however, the first significant increase in C(t) occurs at an earlier time (~105 hours) than that of the cumulative mass (~120 hours). Further testing will be required to determine the significance of this, e.g. whether it might be an artefact of optimising the wavelet to the filtered vibration signal at a particular point in the test, and whether it is repeatable in other experimental tests.

Conclusions

The method proposed in the paper uses Gaussian wavelets to track the degradation of rolling element bearings, and is applied post diagnosis. Vibration and wear debris data obtained from a full-scale test of a helicopter main transmission were used for evaluation. The Gaussian wavelet method was shown to perform well at tracking the degradation of the planet gear bearing for the duration of the test. The results shown in Fig. 4 may well be suitable for fusing vibration and wear debris data to predict the remaining useful life of rolling element bearings.

Acknowledgements

The author acknowledges the School of Mechanical and Manufacturing Engineering, University of New South Wales, Australia for providing the computer code used to filter the test data using the Discrete-Random Separation (DRS) technique.

The author acknowledges Mr Riyazal Hussein from DST Group for providing the cumulative mass of wear debris data from the MetalSCAN sensor recordings.

References

1. El-Thalji, I and Jantunen, E., "A summary of fault modelling and predictive health monitoring of rolling element bearings", *Mechanical Systems and Signal Processing*, Vol. 60, Issue 1, 2015, pp. 252-272.

2. Sawalhi, N and Randall, R.B., "Localised fault detection and diagnosis in rolling element bearings: A collection of state of the art processing algorithms", *Proceedings of the Eighth DSTO international Conference on Health and Usage Monitoring*, AIAC15, Melbourne Australia, 2013.

3. Liu, B. and Ling, S.F., "On the selection of informative wavelets for machinery diagnosis", *Mechanical Systems and Signal Processing*, Vol. 13, Issue 1-2, April 2000, pp. 149-157.

4. Sawalhi, N., Diagnostics, *Prognostics and Fault Simulation for Rolling Element Bearings*, PhD thesis, The University of New South Wales, Australia, 2007.