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ENHANCED UNSUPERVISED NOISE CANCELLATION (E-SANC) USING ANGULAR RESAMPLING
APPLICATION FOR PLANETARY BEARING FAULT DIAGNOSIS

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Summary

In this paper, some techniques of bearing diagnosis are reviewed (unsupervised angular resampling and noise cancellation, envelope analysis) and applied in combination for the first time to solve a particularly difficult diagnostic problem. Unsupervised noise cancellation exploits the periodicity of gear signals. Since, the vibrations from gears are periodic in the angular domain, we propose an enhanced method that uses an unsupervised order-tracking algorithm to perform noise cancellation in the angular domain rather than in the time domain.
This method was then applied to bearing fault diagnosis of a planetary bearing in a helicopter gearbox. Due to random speed fluctuation, unsupervised noise cancellation initially did not separate the gear and bearing signals. However, the enhanced noise cancellation, which includes a pre-treatment to suppress speed fluctuation based on phase demodulation of gearmesh frequencies, without the need for a tacho signal, provides better results. Finally the denoised signal was studied using the envelope analysis technique, and the bearing fault frequency was then detected. Without proper noise cancellation this was not readily detectable in the spectrum noise.

Keywords

Cyclostationarity, Rolling Elements Bearing, Helicopter, Adaptive Noise Cancellation.

Introduction

The bearings of planetary gears provide one of the most difficult scenarios for detection and diagnostics of bearing faults, since the fault signals must pass through a tortuous and time-varying path to arrive at external measurement points where they can be detected. In the case of helicopter gearboxes, this is made even more difficult by the fact that strong background masking signals exist over the full acoustic frequency range, in particular from gears which convert an input shaft frequency at gas turbine speed of typically 350 Hz to a rotor output speed of typically 5 Hz (see Howard [1]).

The first step in analysing bearing signals is to remove the contributions from the gears. Classically, in normal gearboxes, this is done by using a simple band pass filter that exploits their different frequency ranges (see McFadden [2]). However, with helicopter gearbox signals it is usually necessary to first remove the masking signals from gears before the bearing signals can be analyzed. In a previous article by Ho [3] , the self-adaptive noise cancellation technique was used to improve envelope analysis results, but this requires the gear signals to be deterministic, and phase-locked to shaft speeds. If the shaft speeds vary somewhat, it can be necessary to resample the signals on an angular rather than temporal basis (so-called order tracking), to force the gear signals to be deterministic. This normally requires the use of a shaft phase-locked tacho signal to perform the angular resampling.
The aim of this paper is to show how the angular resampling can be performed from the signal itself without the requirement of a tacho signal, thus combining unsupervised noise cancellation with angular resampling (i.e. effectively eliminating the speed fluctuation) to enhance the quality of the separation. A newly developed separation technique is utilized, which is much more efficient than that used in Ho [3]. After presentation of the separation technique, its application to a particularly difficult diagnostic problem is then detailed.

1. Bearing signal separation methods (1 sensor)

Separation methods exploit the different nature of bearing and gear signals. First, we will make a review of some analysis tools (envelope analysis, unsupervised noise cancellation). Next, we will purpose a new method named the enhanced method which combined angular resampling with classic unsupervised noise cancellation and envelope analysis.

1.1 Envelope analysis

In envelope analysis the impulsive nature of roller elements bearing defect is used [3,4]: its energy is distributed widely in the spectrum and weighted by the structural response. Figure 1 illustrates this technique:

- In "simple" gearbox systems (a helicopter gearbox is a counter-example), the contribution of the gears occupies a lower frequency band than that of the bearings. The first step is to choose a band $[f_1, f_2]$ to extract the high frequency bearing contribution. Using a system resonance makes use of the wide dynamic and frequency ranges of the sensors.
- The Fourier transform of the signal is then performed. The content at frequencies between $[f_1, f_2]$ is shifted to $[0, f_2 - f_1]$. The band is doubled by zero padding before inverse Fourier transformation, to ensure that the resulting time signal is analytic. Alternative demodulation techniques, the effect of the zero padding, and masking effects are studied in detail in Ho [3].
- Next, the modulus of the demodulated signal $dem\,(t)$ is taken: $r\,(t) = |dem\,(t)|^m$ with $m = 1$. By using the Fourier transform, the "envelope spectrum" of $r\,(t)$ can be studied in the frequency domain.

A link was found between the squared envelope ($m = 2$) and spectral correlation in Randall [5]. Spectral correlation is a useful tool for cyclostationary signals, that facilitates the identification of links between different frequencies in the spectrum (see Gardner [6]). It has been shown that the Fourier transform of the squared envelope corresponds to the integral of the spectral correlation function over all frequencies in Randall [5]. This means that it contains not only peaks at the basic signal frequencies (links between harmonics) but also peaks due to other linked frequencies (at the differences between any two frequencies eg. sideband spacings).

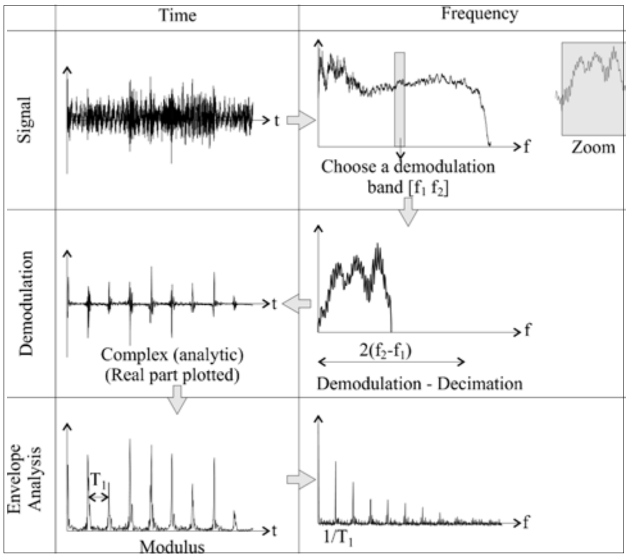


Figure 1 : High Frequency Resonance Technique

1.1 Unsupervised noise cancellation

Unsupervised noise cancellation is based on the statistical properties of the signals rather than their frequency properties. Gears vibrations are due to different sources and mainly the transmission error. Transmission error is the difference between the actual position of the output gear and the position it would occupy if the gear drive were perfect. Transmission error is generated by the periodic meshing stiffness, defaults, ... Since the transmission error is periodic, the vibration will be periodic. In Ho [3], the separation was made by realising that the gear signals are mainly periodic (the non-periodic contribution to the energy of a gear signal is much weaker). This means that each time the gears come back to the same configuration (same teeth in contact), the generated acceleration will be close to that from the previous time. Thus, the gear signal can be predicted by using past values (see Figure 2).

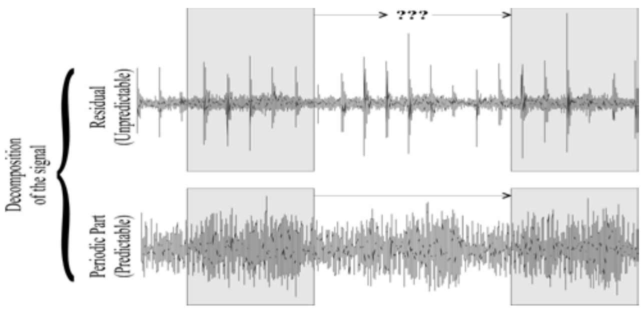


Figure 2 : Decomposition of the signal

Rolling element bearings experiences some slip in the rolling elements, so the impacts never reproduce at the same position. Since the load distribution depends on the angle, rolling element bearings are never submitted exactly to exactly the same load. Moreover, all rolling elements are not strictly identical. These differences introduce some small and random fluctuations around the mean shock period. In Antoni [7], a model for bearing fault signals was proposed :

$$x(t) = \sum_i A_i \cdot s(t - iT_i) + n(t) \quad (1)$$

Where,

- A_i represents the amplitude of the i^{th} impact,
- $s(t)$ is the shape of the impact,
- T_i the time between the i^{th} and $(i-1)^{th}$ impacts (a random process),
- $n(t)$ noise (gear signal, ...).

This model takes account of the random character of bearing signals since the interval between the occurrence of impacts is random within a small distribution. Since a random signal is unpredictable, the occurrence of the next impact cannot be predicted from the past values (see Figure 2). More precisely, in Antoni [7] and Randall [5] it is concluded that the bearing signal is non-stationary stochastic (and has a deterministic quasi-periodic part which is negligible in practice).
Next, the signal $x(t)$ is decomposed into two parts: a predictable periodic part coming from the gears $p(t)$, and another unpredictable part coming from the bearing, and named the residual $r(t)$ (see Figure 2). Let the hat indicate a discrete version of the signal (i.e. $\hat{x}(n)$ is the discrete version of $x(t)$). The principle of unsupervised noise cancellation is to try to predict the discrete version of $x(t)$, $\hat{x}(n)$, by using a linear combination of N previous values $X(n) = [x(n-N+1); \cdots; x(n)]^T$ which are delayed by Δ samples $X(n-\Delta)$ (where n is the index of the discrete time variable), given by :

$$\hat{x}(n) = h^T \cdot X(n-\Delta) \text{ where } h \text{ is an } N \times 1 \text{ vector.} \quad (2)$$

Since the residual is unpredictable (assuming that Δ is large enough to suppress local correlation), we should have, in discrete form,

$$\hat{x}(n) = \hat{p}(n) \text{ and } \hat{r}(n) = x(n) - \hat{x}(n). \quad (3)$$

Theoretically, the length of the filter N should be chosen to be two times the number of discrete frequencies to be tracked. In practice, when noise is added, the bigger the value of N, the sharper will be the discrete frequency extraction filter. The delay Δ should be large enough to suppress any correlation between the residual (random) signal and its delayed version. Nevertheless, since the signal is not strictly periodic, Δ should be short enough to remain within the correlation length of the deterministic part.
These equations can be solved rapidly by using a frequency domain algorithm (see Antoni [9]). In the frequency domain, we can transform Eq. (6) into the following relation:

$$S_{X(n),X(n-\Delta)}(f) = H(f) \cdot S_{X(n-\Delta),X(n-\Delta)}(f) \quad (4)$$

Where $S_{A,B}(f)$ is the cross-power spectrum between A and B (with included weighting), and $H(f)$ the Fourier transform of $h(t)$.
As illustrated in Figure 3, both the cross and auto spectra are computed for each block of the signal. Next, an estimation is made by averaging respectively the local cross and auto spectra. Then, the filter is deduced by dividing the cross spectrum by the auto spectrum at each frequency. It is assumed that the case of zero power in any frequency band in the auto spectrum should not exist since we use real signals that contain noise.

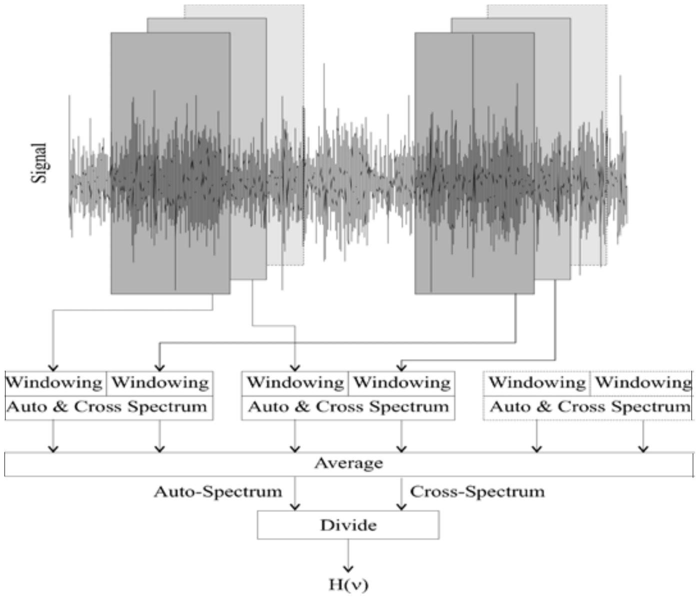


Figure 3 : Frequency domain unsupervised noise cancellation

A complete study of these algorithms can be found in Antoni [8] and [9] (for the frequency domain version).
The main problem with this method is that the gear signal is periodic in the angular domain and the signals are generally recorded against time. It works when the speed fluctuation is sufficiently small, but if it gets bigger, the periodic part cannot be extracted properly. Another well known type of signal separation in the angular domain is synchronous averaging (see McFadden [10]), but this can only separate one periodic signal at a time.

1.3 Enhanced method

Since speed fluctuations can cause problems with unsupervised noise cancellation, the idea is to reduce these speed fluctuations by working in the angular domain. Unfortunately, the signal is in the time domain and tachometer signals are not always available. Therefore, the resampling is done by extracting the speed information from the acceleration signal itself [11]. Figure 4 illustrates the resampling algorithm.

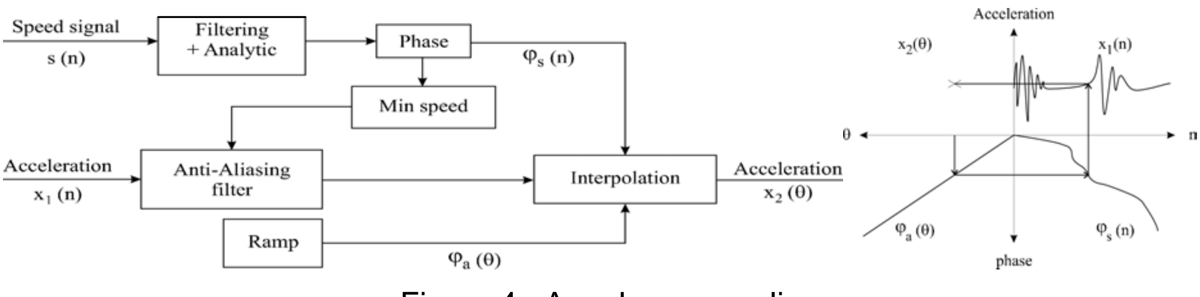


Figure 4 : Angular resampling

First, the speed related signal $s(n)$ (acceleration signal in this case) is filtered around a meshing frequency that fluctuates proportionally to shaft speed. Next, by using the analytic signal it is possible to estimate the phase $\varphi_s(n)$ (i.e. the angular position of a shaft) and the instantaneous speed. Since we resample the signal, we must take care of the Nyquist frequency requirements. That is why we use the minimum speed

(which corresponds to the lowest sampling frequency) to set up a software anti-aliasing filter (if needed). Interpolation enables us to convert acceleration $x_1(n) = s(n)$ for an estimated phase $\varphi_s(n)$ (shaft position) to acceleration $x_2(n)$ at constant angle increments $\varphi_a(\theta)$ (linear phase).
Next, we extract the residual signal (i.e. rolling element bearing contribution) by using unsupervised noise cancellation on the angular domain resampled signal. By performing the inverse process, it is possible to come back to the temporal domain if needed.
The diagnosis method could be applied either in the temporal domain or in the angular domain. If the gearbox is complex, it could be of interest to use this algorithm for a range of different meshing frequencies.
Envelope analysis techniques will be applied to this signal after separation and speed correction. Other diagnosis techniques exist and can be found in Howard [1].

2. Helicopter Gearbox Signals

This study is based on Sea Hawk helicopter gearbox signals. The signals were supplied by the US Naval Air Warfare Center, Aircraft Division, Trenton (New Jersey) who made a series of vibration measurements on a gearbox test rig. Acceleration was sampled at $f_s = 100\ kHz$ for $60\ s$ ($N = 6 \cdot 10^6\ samples$).
The acceleration signal recorded by the sensor at the Port Ring point at a load of $400\ ftlb$ was used for the following analysis. Figure 5 shows a sketch of the transmission.

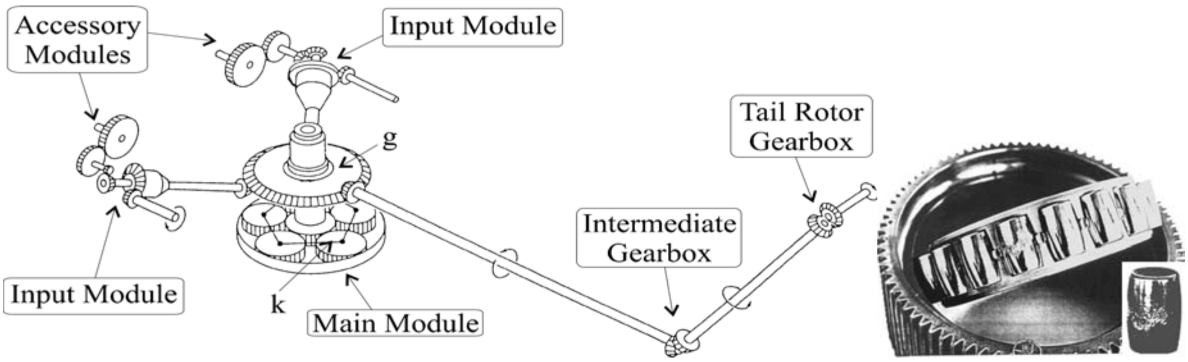


Figure 5 : Sketch of the transmission - Photo of the spalled roller

The known fault in the gearbox under test consisted of a spalled roller in one of the planetary bearings.

3. Application of the techniques

3.1 Look at the signal

Figure 6 shows the first $10,000$ samples ($100\ ms$) of the signal. 7 shocks occur during this time. Since, these shocks cannot be detected visually, the bearing contribution is totally masked by the rest of the signal and some processing is needed.

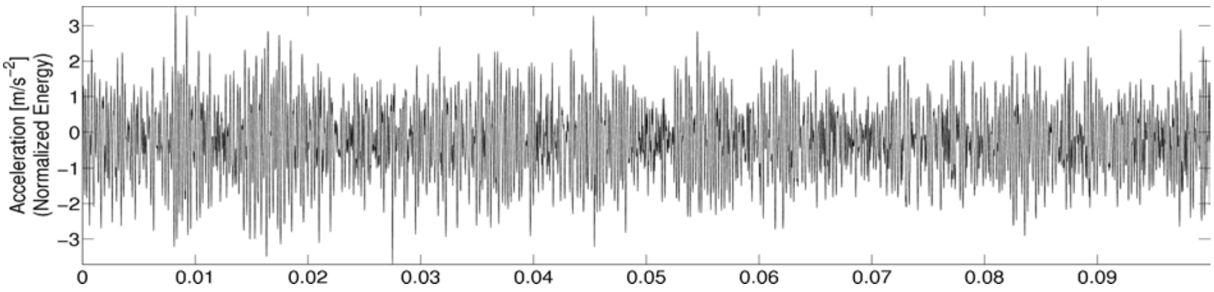
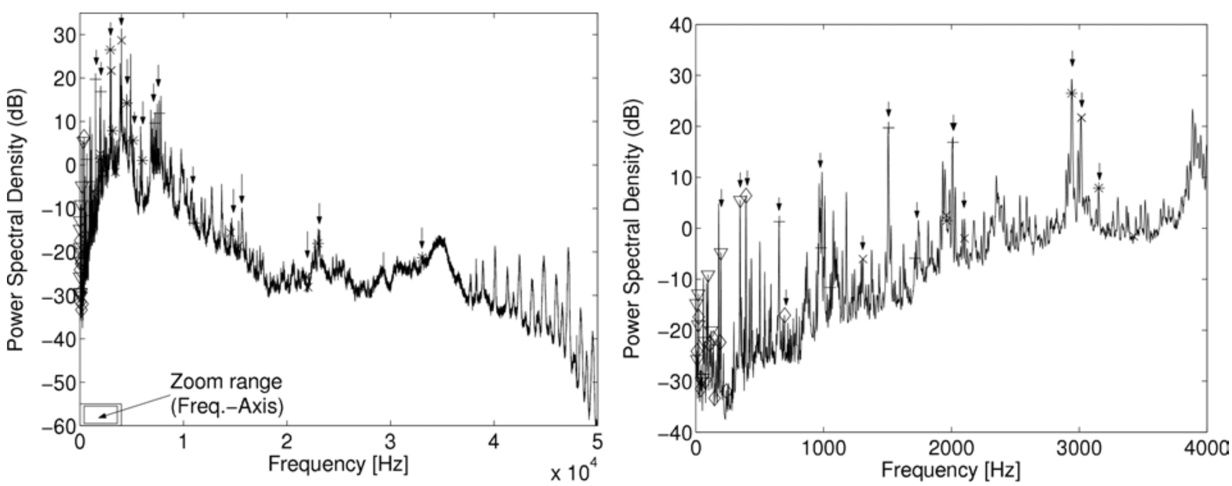


Figure 6 : First samples

Figure 7 shows the power spectral density of the signal in two frequency bands. Each group of symbols corresponds to rotation frequencies (triangles), their second harmonics (diamonds), meshing frequencies and their harmonics (pluses, crosses, asterisks). By looking at the spectrum an aliasing problem can be seen above $35\,kHz$, so higher frequencies will not be considered. It is possible to see third meshing frequency harmonics (asterisks) near $23\,kHz$ and above. This therefore confirms the problem of the wide distribution of the gear signals. It also suggests attempting the unsupervised noise cancellation method.

Harmonic used for demodulation

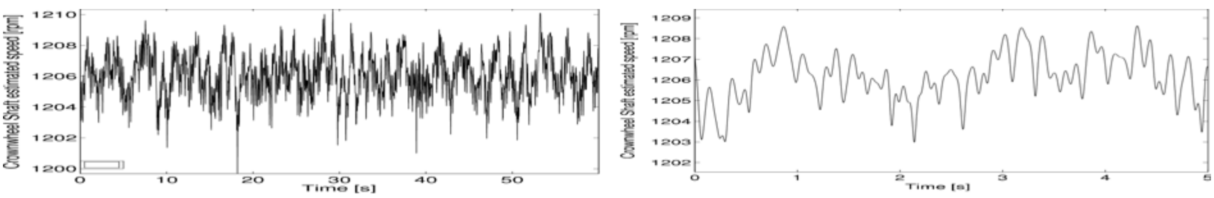


(a) full scale (b) zoom

Figure 7 : Signal spectrum

3.2 Unsupervised noise cancellation

First, the classical noise cancellation technique was applied to the signal. The tested delays were from $10\,ms$ ($\Delta = 1024$ samples) to $2.6\,s$ ($\Delta = 262144$ samples), with the window size $0.66\,s$ ($N = 65536$ samples). Whatever the value of Δ is, results are identical. Figure 9 shows two frequency ranges of the processed signal spectrum (periodic part removed) as a full line and comparison with the original signal, dotted line, for $\Delta = 70000$ and $N = 65536$. The original signal has been shifted up by 30 dB to make the comparison easier.
It is obvious that unsupervised noise cancellation does not work in this case (above $300\,Hz$) since it does not remove "discrete" frequencies coming from the gears (see symbols in Figure 7). The same kind of results were obtained for many other sets of parameters. Figure 8 shows the Crownwheel Shaft speed estimation (for the whole signal and for the first 5 seconds) using the analytic signal method (applied to the band $1.5\,kHz$ to $1.52\,kHz$). Since the estimation is based on the analytic signal, it suppresses all speed fluctuations greater than $20\,Hz$. The speed fluctuation represents $0.9\,\%$ of the mean speed. Such speed fluctuation could disturb the unsupervised noise cancellation algorithm. A spectrum show that speed fluctuation contains harmonics of the Planet Carrier Frequency.

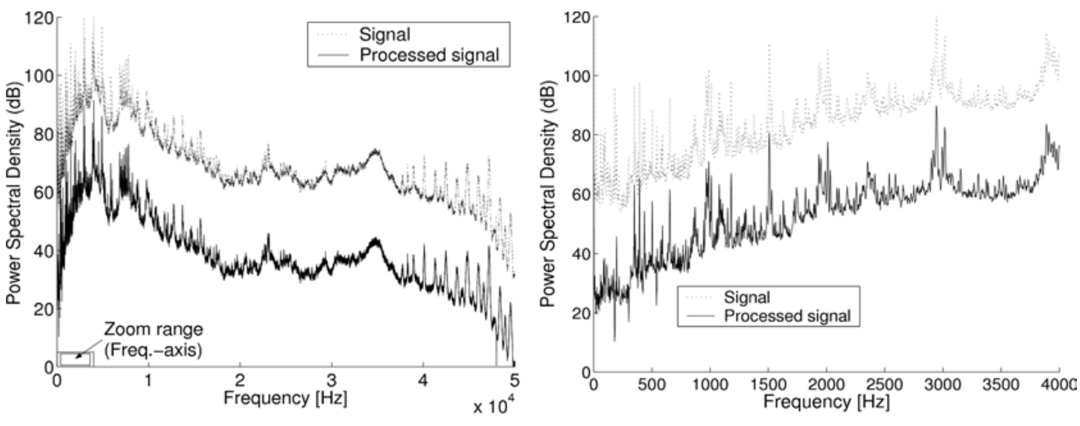


(a) whole signal (b) first 5 seconds (zoom)

Figure 8 : Crownwheel shaft speed

3.3 Enhanced unsupervised noise cancellation

Since the speed fluctuation gave problems with unsupervised noise cancellation, its effect was reduced by using angular resampling [11]. An enhanced algorithm based on the meshing frequency of the crownwheel shaft at $1509\,Hz$ was used. In the processed signal spectrum, a reduction of some discrete components was observed.



(a) full scale (b) zoom

Figure 9 : Spectrum after noise cancellation

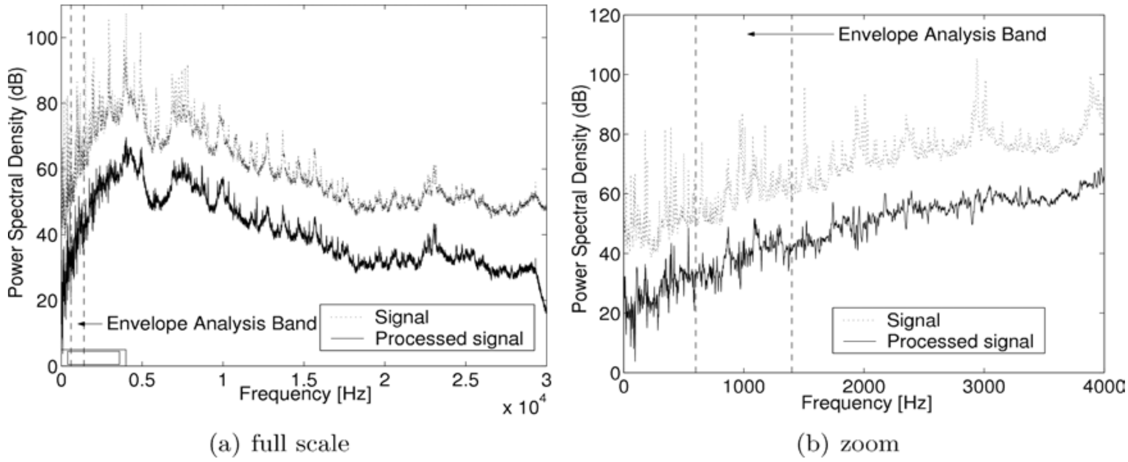


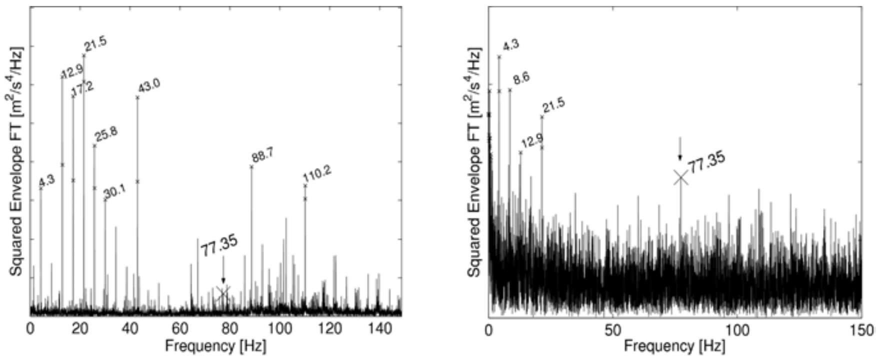
Figure 10 : Spectrum after enhanced unsupervised noise cancellation

Figure 10 shows the improvement in the power spectrum after the enhanced unsupervised noise cancellation. In the low frequency area, there is a reduction of discrete frequency components of between 5 and $25\ dB$. Above $18\ kHz$ it seems that there is only attenuation, and no removal of discrete frequency components. Thus, the benefit of the unsupervised noise cancellation will primarily be at lower frequencies, since there is no reduction of discrete frequencies in the high frequency range. Therefore, envelope analysis will be improved in this area.
No link should be made between the frequency used for enhanced unsupervised noise cancellation and the one used for envelope analysis. It should only be checked that enhanced unsupervised noise cancellation "cancels" gear harmonics in the envelope analysis band.

3.4 Envelope analysis

To make the envelope analysis curves easier to compare, they are normalized by the value at the frequency $77.359\ Hz$ (the roller fault frequency). Traditionally, the band for envelope analysis would be chosen by looking at spectrum changes for different degrees of degradation. Since we only had one record, we used trial and error by taking a band of $800\ Hz$ and shifting it in steps of $500\ Hz$. It was found that the band from $600\ Hz$ to $1400\ Hz$ was suitable for the envelope analysis since the fault frequency was clearly visible (see Figure 11).

Figure 11 compares the envelope analysis before and after attenuation of the gear signal by the enhanced noise cancellation method. The large cross corresponds to the roller bearing fault. Prior to using noise cancellation, the fault frequency is very difficult to detect, whereas the use of the noise cancellation makes it easy to distinguish. The envelope spectrum after using the noise cancellation method in the time domain makes no improvement (same result than Figure 11a) and justifies the use of the enhanced version.



(a) F.T. of the squared envelope of the original signal (b) F.T. of the squared envelope of the denoised signal

Figure 11 : *Effect of unsupervised noise cancellation (squared envelope – original, denoised)*

Conclusion

This article has reviewed how the envelope analysis and unsupervised noise separation techniques work to enhance the detection and diagnosis of bearing faults. It also proposed the use of angular resampling (based on gearmesh components rather than a tacho signal) to enhance the unsupervised noise cancellation method where some random speed variation exists. The enhanced method was next applied to a helicopter gearbox signal, where unsupervised noise separation did not work properly without compensation for speed variation. The example shows the efficiency of the enhanced method and at the same time its limitations at high frequencies. Envelope analysis clearly shows a peak corresponding to the roller fault frequency. Consequently, this method gives an alternative way to perform envelope analysis for signals where classical envelope analysis and unsupervised noise cancellation do not work, and where a tacho signal is not available. It can improve the results but has some limitations.

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