Vibration and Electrical Interference Removal for Improved Bearing Fault Diagnosis

Iman Soltani Bozchalooi and Ming Liang

Department of Mechanical Engineering
University of Ottawa
770 King Edward Avenue, Ottawa, Ontario, Canada, K1N 6N5

ABSTRACT

The bearing vibration signal contains important information for bearing health assessment. However, the measured signal is often heavily clouded by various noises due to the compounded effect of interferences of other machine elements and background noises. Therefore, reliable condition monitoring would not be possible without proper de-noising. This paper presents a new de-noising scheme to enhance the vibration signals acquired from faulty bearings. This de-noising scheme features a spectral subtraction to trim down the in-band noise prior to wavelet filtering. The Gabor wavelet is used in the wavelet transform and its parameters, i.e., scale and shape factor are selected in separate steps. The proper scale is found based on a novel resonance estimation algorithm. The shape factor value is then selected by minimizing a smoothness index. De-noising results are presented for experimental data acquired from a faulty bearing with defective outer race.

1. INTRODUCTION

Monitoring and diagnosis of the health of machinery elements has attracted much attention over the past few decades [1]. One of the important approaches in this area of research is based on the analysis of the vibration data measured through the accelerometers mounted on or near the critical mechanical components. However, the main problem affecting the performance of the fault diagnosis methods is the corrupting noise. As a result, an effective de-noising method would be necessary to remove such corrupting noise and interferences.

Two major de-noising approaches namely wavelet threshold based (also known as decomposition based) [2] and wavelet filter based [3-6] have been used to purify the vibration signals measured from faulty bearings or gears. The studies reported in [3, 4] are in favour of the wavelet filter based de-noising. However, the performance of this de-noising scheme is greatly affected by the wavelet parameter selection strategy. We propose a new approach for the selection of the Gabor wavelet parameters namely scale and shape factor as they define the center frequency and the bandwidth of a Gaussian filter respectively. The first step of the selection process consists of a resonance frequency estimation algorithm. The estimation result leads us to a desirable scale value. Shape factor value associated with the selected scale is then found by minimizing a smoothness index (SI). Though the filtering process, if performed properly, can increase the SNR of the measured vibration, the in-band noise with frequency content in the range covered by the bandpass filter is not eliminated. For this reason, we propose to apply spectral subtraction [7, 8] prior to bandpass filtering such that certain in-band noise can be removed.

This paper hereafter is organized as follows. Section 2 provides a brief overview of the wavelet transform and the wavelet filter based de-noising method. The proposed wavelet parameter selection methods are presented in section 3. Section 4 details the spectral subtraction technique as a mean to improve the performance of the wavelet filter based de-noising method. The proposed algorithm is then experimentally evaluated using a faulty bearing with damaged outer race in Section 5. Section 6 concludes the paper.

2. SIGNAL ENHANCEMENT USING AN ADAPTIVE WAVELET FILTER

A major de-noising approach is bandpass filtering. In this method the high SNR frequency band of the signal is passed through the filter and other frequency components are discarded. Due to the resonance excited by the fault impacts, such a high SNR band also exists for the vibration signal measured from faulty bearings. By bandpass filtering the measured vibration signal around this frequency band the impulsive features of these signals can be more clearly identified. One filtering method would be wavelet transforming the signal at a fixed scale. The continuous wavelet transform (CWT) of \( f(t) \) with respect to a mother wavelet \( \psi(t) \) is obtained by [9, 10]:

* Corresponding author: Tel.: (613) 562-5800 ext. 6269; Fax: (613) 562-5177; E-mail: liang@eng.uottawa.ca
\[
W_f(s,u) = \int_{-\infty}^{\infty} f(t)\psi^*_s(t)dt
\]

where \(\psi_s(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)\), s and u are real and asterisk stands for complex conjugate.

A close look at Eq. (1) shows the resemblance of this equation to the convolution process. Hence, we can write:

\[
F_s[W_f(s,u)] = F_s[f(u)]F_s[\psi^*_{s,0}(-u)]
\]

where \(F_s\) denotes Fourier transform of a function with respect to variable x. According to Eq. (2) the wavelet transform \(W_f(s,u)\) for a fixed scale can be interpreted as a filtering process using a filter with an impulse response equal to \(\psi_{s,0}(t)\) [10]. Due to its optimum time and frequency resolutions, we choose Gabor wavelet as the mother wavelet. The Gabor wavelet is defined as:

\[
\psi(t) = ce^{-\sigma^2t^2}e^{i2\pi ft}
\]

Eqs. (2) and (3) lead to:

\[
F_s[W(s,u)] = \sqrt{s}F_s[f(u)]\tilde{\psi}^*(sf)
\]

where \(\tilde{\psi}(f)\) is the Fourier transform of \(\psi(t)\) and can be written as:

\[
\tilde{\psi}(f) = c\sqrt{\frac{\pi}{\sigma^2}}e^{-\left(\frac{\pi^2}{\sigma^2}\right)(f-f_0)^2}
\]

The last two equations imply that for a constant scale, the Gabor wavelet transform acts as a bandpass filtering process with a Gaussian filter. The bandwidth and center frequency of this filter can be adjusted by changing shape factor \(\sigma\) and scale \(s\), respectively. Furthermore, it can be shown that the filtered signal given by the wavelet transform at a fixed scale will be analytic if \(\frac{(\pi f_0)^2}{\sigma^2} \gg 1\) [9]. Therefore, the modulus of this analytic result would provide the envelope of the bandpass filtered signal [6, 9]. Denoting the Gabor wavelet transform of a signal \(V(t)\) at scale \(s\) and shape factor \(\sigma\) by \(W^{s,\sigma}_V(u)\), the envelope of the bandpass filtered \(V(t)\) is obtained by

\[
\left|W^{s,\sigma}_V(u)\right| = \sqrt{\left(\text{Re}\left(W^{s,\sigma}_V(u)\right)\right)^2 + \left(\text{Im}\left(W^{s,\sigma}_V(u)\right)\right)^2}
\]

3. WAVELET PARAMETER SELECTION

3.1 SCALE SELECTION

It is well known that the frequency band corresponding to the resonance excited by the fault impacts forms the high SNR band of the vibrations measured from faulty bearings. Accordingly, a resonance frequency estimation method should provide a proper scale value. Figure 1(a) shows a portion of the simulated faulty bearing vibrations. Such vibrations form a periodic signal. Each period contains two ranges: a Resonance Active Range (RAR) and a Resonance Inactive Range (RIR) (Figure 1(a)). When the shaft speed goes up, the RAR length remains unchanged or generally increases due to the increased impact intensity. This observation suggests that the RAR comprise an increased portion of a period when the shaft speed increases (Figure 1(a) and (b)). On the other hand, for \(f(t) = a(t)\cos \varphi(t)\), the instantaneous frequency of \(f(t)\) is given by \(\varphi(t)\) [11]. Considering the fault generated impulse modelled as \(S(t) = Ae^{-\beta t}\cos(\omega_0 t)u(t)\), where \(u(t)\) is the units step function, the instantaneous frequency found for the signal interval associated with the RAR length would be equal to the excited resonance frequency \(\omega_0\). Hence, when the shaft speed increases an instantaneous frequency that corresponds to the largest proportion
increase can be identified as the resonance frequency. To implement the above idea, we form the empirical probability density of the instantaneous frequency for two vibration datasets measured from the same bearing at two different rotational frequencies. With an increase in the rotational speed, we expect a larger probability increase for the resonance frequency compared to the other frequencies.

To elaborate, we define \( \varphi_m^T(n) \) as the instantaneous frequency of the vibration signal measured at sampling frequency \( \frac{1}{T} \), rotational speed \( \omega_m \) and at sampling time \( nT \). We further denote the empirical probability density function of \( \varphi_m^T(n) \) \( (n = 1...N) \) by \( \text{Pr}_m^T(f) \) given as \( \text{Pr}_m^T(f) = \frac{N_f}{N} \), where \( N_f \) is the number of samples with instantaneous frequency of \( \varphi_m^T(n) = f \), and \( N \) is the total number of samples. Following a rise in the shaft rotational speed, the probability density change for each frequency will be:

\[
\Delta \text{Pr}_{i,j}^T(f) = \text{Pr}_j^T(f) - \text{Pr}_i^T(f) \quad \text{for} \quad \omega_j > \omega_i
\]

Then the resonance frequency can be identified as:

\[
f_{\text{res}} = \arg \max_f \left[ \Delta \text{Pr}_{i,j}^T(f) \right], \quad \text{where} \ f_{\text{res}} \ \text{is the estimated resonance frequency.}
\]

The scale associated with the above identified resonance frequency will then be used for the de-noising process.

3.2 SHAPE FACTOR SELECTION

Since bandpass filtering is usually treated as a pre-processing step for envelope spectrum analysis [1], we can use the characterizing nature of this envelope to adjust the shape factor or the bandwidth of the corresponding bandpass filter. A criterion for this adjustment is the smoothness of the envelope of the bandpass filtered result. A robust index quantifying such a characteristic is the ratio of the geometric mean to the arithmetic mean, i.e., smoothness index (SI). This index has been used as a measure of spectral flatness in speech signal processing [12] and is defined as:

\[
r_{G/A} = \left( \frac{\prod_{n=1}^{N} S(n)}{\sum_{n=1}^{N} S(n)} \right)^{\frac{1}{N}}
\]

for a positive time series \( S(n) \). \( r_{G/A} \) is always in the range of [0,1] for a positive time series. A useful property of \( r_{G/A} \) is that it approaches unity for smooth time series and drops to zero for a highly impulsive series. When the shape factor value is properly adjusted and consequently, the fault generated impulses can be clearly detected, we
expect the envelope of the bandpass filtered signal to form a more impulsive time series. Replacing \( S(n) \) in Eq. (7) by the expression given in Eq. (6), \( \eta(\sigma) \) can be written as
\[
\eta(\sigma) = \left( \prod_{n=1}^{N} |W_{n}^{p}(nT)| \right)^{\frac{1}{N}} \sum_{n=1}^{N} |W_{n}^{p}(nT)| \tag{8}
\]
where \( S_{p} \) is the selected scale, \( T \) the sampling period and \( N \) the number of samples. Accordingly, the proper shape factor value can be found by minimizing \( \eta(\sigma) \).

4. SPECTRAL SUBTRACTION

In the previous section an adaptive filtering approach was proposed. However, through this method the noise components contained in the frequency band of the filter would not be removed. Therefore, the quality of the denoising result may still be affected by such noises. To offset such a drawback of the wavelet filter-based de-noising method, spectral subtraction can be used prior to wavelet transform. Spectral subtraction has been widely used in speech signal processing [7]. In this method the PSD (Power Spectral Density) of the pure signal is estimated. This estimate is then used to reconstruct the enhanced signal. As explained before the frequency band that would pass through the filter corresponds to the resonance excited by the fault impacts. Such impacts usually excite a resonance in the system at much higher frequency than the vibration generated by other machine elements [1]. Therefore, it is reasonable to assume that the major part of the in-band noise consists of the background noise present in the measurement device and mainly caused by the wiring flaws and electrical interferences. To elaborate, we consider:
\[
V(t) = v(t) + N_1(t) + N_2(t) \tag{9}
\]
where \( V(t) \) is the measured vibration, \( v(t) \) is faulty bearing vibration, \( N_1(t) \) is the measured noise caused by other vibration (e.g., shaft imbalance, gear meshing, etc.) and \( N_2(t) \) is the background noise due to wiring flaws and electrical interferences, uncorrelated with \( v(t) \) and \( N_1(t) \). From (9), we have:
\[
|\hat{V}(\omega)|^2 = |\hat{v}(\omega) + \hat{N}_1(\omega)|^2 + |\hat{N}_2(\omega)|^2
\]
According to this equation, with an estimate of \( |\hat{N}_2(\omega)|^2 \), \( |\hat{G}(\omega)|^2 = |\hat{v}(\omega) + \hat{N}_1(\omega)|^2 \) can be estimated by:
\[
|\tilde{G}(\omega)|^2 = |\tilde{V}(\omega)|^2 - |\tilde{N}_2(\omega)|^2 \tag{10}
\]
where \( \tilde{N}_2(\omega) \) and \( \tilde{G}(\omega) \) are estimates of \( \hat{N}_2(\omega) \) and \( \hat{G}(\omega) \) respectively. Given \( |\tilde{G}(\omega)| \), an estimate of \( |\tilde{v}(\omega) + \hat{N}_1(\omega)| \) to estimate \( v(t) + N_1(t) \) the phase information is also required. We assume that the phase information is relatively unimportant so that we can approximate \( \angle(\hat{v}(\omega) + \hat{N}_1(\omega)) \) by \( \angle(\hat{V}(\omega)) \).

As the spectral subtraction is concerned with the in-band noise which would usually correspond to a narrow frequency band, it is reasonable to assume that the energy of the background noise \( N_2(t) \) is uniformly distributed over such a narrow band. Consequently, we can further assume \( N_2(t) \) as white. This assumption will simplify the analysis since the PSD of such noise is flat over the frequency domain and can be represented with a single value for all frequencies. As a result, subtraction of this constant value from the PSD of the measured signal would provide us with an estimate of \( \hat{G}(\omega) \). Furthermore, we can apply the smoothness minimization criterion introduced earlier to find the proper subtraction value. A discretized range of values \([N_{\min}, N_{\max}]\) are considered for \( |\tilde{N}_2(\omega)|^2 \). The value on this range which minimizes the SI calculated for the envelope of the spectral subtracted signal is chosen as the best estimate for \( |\tilde{N}_2(\omega)|^2 \). As Eq. (10) also yields negative values, it is modified as follows to ensure a non-negative result:
\[ |\tilde{G}(\omega)|^2 = \begin{cases} |\tilde{V}(\omega)|^2 - |\tilde{N}_2(\omega)|^2 & \text{for } |\tilde{V}(\omega)|^2 > |\tilde{N}_2(\omega)|^2 \\ 0 & \text{Otherwise} \end{cases} \]  

(11)

Finally, \( v(t) + N_1(t) \) is estimated using: 
\[ \tilde{G}(\omega) = |\tilde{G}(\omega)| \exp \left( j \omega \right) \] and
\[ \tilde{G}(t) = F^{-1} \left[ \tilde{G}(\omega) \right] \]  

(12)

Following the spectral subtraction step, the reconstructed time signal given by Eq. (12) is wavelet transformed using the scale and shape factor values found through the wavelet parameter selection algorithms explained in previous sections to eliminate \( N_1(t) \).

5. EXPERIMENTAL EVALUATION

The proposed method is evaluated by de-noising signals of a faulty bearing with outer race fault. The experiment is conducted using a SpectraQuest Machinery Fault Simulator (MFK-PK5M) (Figure 2). Two well balanced mass rotors (2" thick, 4" in diameter and 11.1 lbs each) are installed on a 5/8" steel shaft and supported by two bearings of type ER10K. The simulator is powered by a 3-hp AC motor that is controlled by a Hitachi drive (SJ200-022NFU). The shaft speed was 630 RPM (10.5Hz). The left bearing has a pre-seeded fault on the outer race with a characteristic frequency of 32 Hz (= 3.052 \( \omega \)). An accelerometer (Montronix VS100-100) with 100 mV/g sensitivity and 1-12 kHz sensitivity range is used to collect the signal. The signal is fed to an NI AT-MIO-16DE-10 DAQ card and then collected via LabVIEW. The signal processing is done using MATLAB on a Pentium® 4/2.52GHz PC.

To create additional vibration interference, a gearbox is also connected to the driving shaft using a belt as shown in Figure 2. The vibration signal is sampled at 20000 samples/sec. Part of the raw data and the corresponding de-noised result are plotted in Figure 3. To select the scale using the resonance frequency estimation algorithm, an additional vibration signal is acquired at 780 RPM (13Hz) rotational speed. The proper \( (s-\sigma^2) \) combination is found as \((50, 0.32)\) and the minimum SI is 0.7398. As shown in the figure the time interval between two consecutive impulses is about 0.0313 seconds which precisely reflects the fault characteristic frequency of 32Hz.

6. CONCLUSION

In this paper, a de-noising scheme was suggested to enhance faulty bearing signals. The algorithm involves two steps: spectral subtraction and wavelet filtering. The main purpose of spectral subtraction is to reduce the in-band noise with frequency content that is the same as the frequency band covered by the daughter Gabor wavelet. The resulting time domain signal is then wavelet transformed to eliminate the interfering vibration signal from other sources, e.g., shaft imbalance, gear meshing, etc. To find the desirable scale value, a resonance frequency estimation
algorithm is developed. Corresponding to the selected scale, a proper shape factor is then determined in a separate step by minimizing a smoothness index (SI) calculated for the wavelet coefficient moduli. The proposed method has been successfully applied to de-noise signal measured from a bearing with outer race fault.

![Figure 3. (a) Vibration signal measured at 630 rpm rotational speed, (b) De-noising result.](image)

ACKNOWLEDGEMENT

The major part of this study was supported by Natural Science and Engineering Research Council of Canada. Their support is greatly appreciated.

REFERENCES


