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Fault Diagnosis in Bearing Housings Using Wavelet Transform

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Abstract. The early and accurate diagnosis of bearing housing defects in industrial equipment is essential to ensure the reliability and operational efficiency of rotating components, preventing unscheduled downtimes. This study presents the wavelet transform as an effective technique for analyzing vibration signals from operational bearing housings, enabling the identification and characterization of faults at incipient stages. Due to its capability for multiresolution analysis, offering joint time-frequency representation, the wavelet transform is well-suited for detecting transients and irregularities associated with mechanical failures. Various wavelet families were evaluated for signal decomposition, facilitating the extraction of discriminative features that aid in distinguishing between normal and faulty conditions. The orthogonal decomposition achieved through the transform during signal processing highlighted early fault indicators while suppressing system noise. The results demonstrate that this approach significantly enhances predictive monitoring systems, improving diagnostic accuracy in industrial machinery. Thus, the application of the wavelet transform proves to be a robust and promising alternative for detecting transients and characteristic fault frequencies in the initial stages of bearing housing failures, supporting real-time decision-making and improving operational reliability.

Keywords: Fault diagnosis; ball bearings; wavelet; envelope analysis; FFT.

1 Introduction

The reliability of rotating equipment is one of the pillars of industrial efficiency. According to Harris [1], more than half of industrial machinery failures are associated with defects in rolling element bearings. Early detection of such faults enables scheduled maintenance, preventing catastrophic damage and optimizing component lifespan.

Vibration analysis techniques for rolling bearings have been applied in industrial environments for several decades. Implemented signal processing tools vary widely, such as global RMS value measurements, which, despite limitations in pinpointing defect location and wear level, offer speed and practicality in defect detection [2]. According to Barilli [3], spectral analysis implementation is generally more efficient for identifying the onset of defects, particularly when monitoring allows tracking of fault progression. As noted by Al-Badour [4], the acceleration envelope functions as an observation window for the passage frequencies of bearing rolling elements through components such as the inner ring, outer ring, and cage, modulated by their respective natural frequencies. This method, when combined with Fast Fourier Transform (FFT), enables observation in the frequency domain of the magnitudes of these micro-impacts [5].

With the advent of Industry 4.0 technologies such as IoT and AI, the demand for more effective monitoring techniques has grown. In this context, this study investigates the application of the wavelet transform in the analysis of vibration signals from rolling bearings, aiming to identify faults at early stages.

2 Modeling and Simulation

The theoretical model corresponds to the NSK manufacturer's self-aligning ball bearing 1207 K bearing and was represented as a mass-spring-damper system to simulate the dynamic responses of its components. For the inner ring, outer ring, and cage, the model followed Timoshenko's method [7], where the ring is considered narrow enough for the analysis to be carried out in a purely radial, Fig. 1 shows the cross-sectional representation.

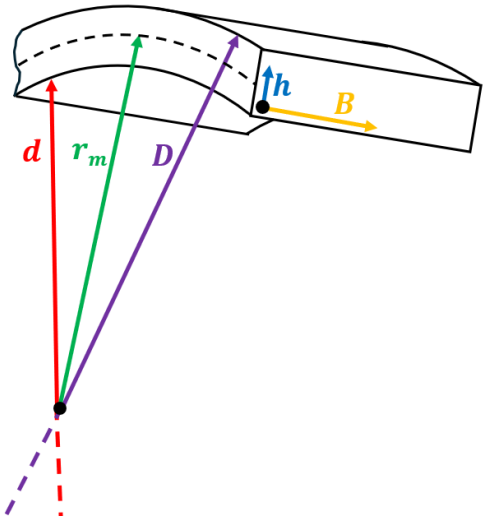


Figure 1. Schematics applied to the models of inner ring, outer ring, and cage.

The simplified model for determining the natural frequency of the ring is given by:

$$f_n = \frac{n\,(n^2-1)}{2\pi r_m^2}\sqrt{\frac{E\,I}{\rho\,A}}, \tag{1}$$

where n is the mode number, r_m the mean radius of the ring, E the modulus of elasticity of the material, I the moment of inertia, ρ the density, and A the cross-sectional area. The cross-sectional area is calculated as:

$$A = B\,h\,, \tag{2}$$

where h is:

$$h = \frac{D-d}{2}. \tag{3}$$

The axis for evaluating the effect of the moment of inertia is called the mean radius and can be obtained as:

$$r_m = \frac{D+d}{4}. \tag{4}$$

The moment of inertia can be calculated as:

$$I = \int_{-\frac{B}{2}}^{+\frac{B}{2}}\int_{-\frac{B}{2}}^{+\frac{B}{2}} h^2\,dh\,dB\,, \tag{5}$$

which simplifies to:

$$I = \frac{B\,h^3}{12}.$$

With these data, it was possible to estimate the natural frequencies of the elements for modeling and simulation, as shown in Tab. 1.

Table 1. Calculated natural frequencies of the bearing rings

Description	Symbol	Value	Unit
Natural frequency of inner ring	f_{iner}	~ 4,700	Hz
Natural frequency of outer ring	f_{outer}	~863	Hz
Natural frequency of cage	f_{cage}	~698	Hz

The characteristic frequencies associated with different bearing elements [5] are:

$$BPFI = \frac{Zfi}{2}\left(1 + \frac{dcos(\alpha)}{D}\right), \tag{6}$$

$$BPFO = \frac{Zfi}{2}\left(1 - \frac{d\,cos(\alpha)}{D}\right), \tag{7}$$

$$2BSF = 2\left(\frac{fiD}{2d}\left(1 - \left(\frac{dcos(\alpha)}{D}\right)^2\right)\right), \tag{8}$$

$$FTF = \frac{fi}{2}\left(1 - \frac{d\,cos(\alpha)}{D}\right). \tag{9}$$

where $BPFI$ = Ball Pass Frequency Inner, $BPFO$ = Ball Pass Frequency Outer, $2BSF$ = Twice Ball Spin Frequency, and FTF = Fundamental Train Frequency.

Table 2. Input data for calculating characteristic frequencies

Description	Symbol	Value	Unit
Differential rotation frequency	fi	1746	rpm
Number of rolling elements per raceway	Z	16	-
Pitch diameter (inner raceway)	d	44.960	mm
Pitch diameter (outer raceway)	D	60.840	mm
Contact angle of element on raceway	α	0	°

The values found for each characteristic frequency are presented in Tab. 3.

Table 3. Bearing characteristic frequencies

Description	Symbol	Value	Unit
Inner raceway pass frequency	$BPFI$	~ 267.7	Hz
Outer raceway pass frequency	$BPFO$	~ 197.9	Hz
Twice ball spin frequency	$2BSF$	~189+.6	Hz
Fundamental Train Frequency	FTF	~12.4	Hz

2.1 Digital Signal Processing

Simulated signals were generated with periodic excitation modulated by the natural frequency of the outer ring (Tab. 2), corresponding to typical fault transients. These signals can be seen in Tab. 3 and are shown plotted in the time domain in Fig. 2. The entire digital signal processing stage for both the simulated and real signals was developed in Python, with the implementation of the equations and tools presented in this work but using libraries already available on the platform.

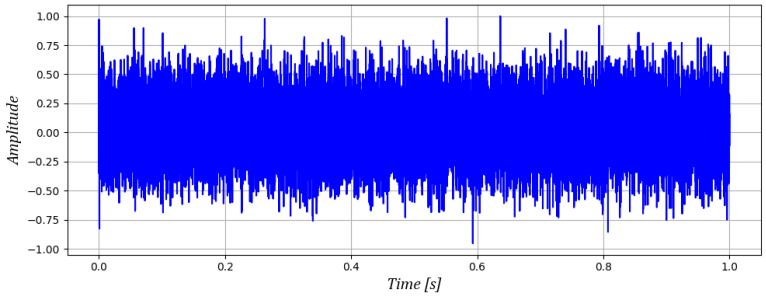


Figure 2. Simulated time signal with transients of the bearing characteristic fault frequencies and white noise.

Frequency-domain analysis can be performed using the FFT as:

$$X_{(f)} = \int_{-\infty}^{\infty} x_{(t)}.e^{-j2\pi ft}dt\,, \tag{10}$$

where $X_{(f)}$ represents the signal in the frequency domain, $x_{(t)}$ the signal in the time domain, and $e^{-j2\pi ft}$ the complex exponential basis. The signal in the frequency domain can be seen in Fig. 3.

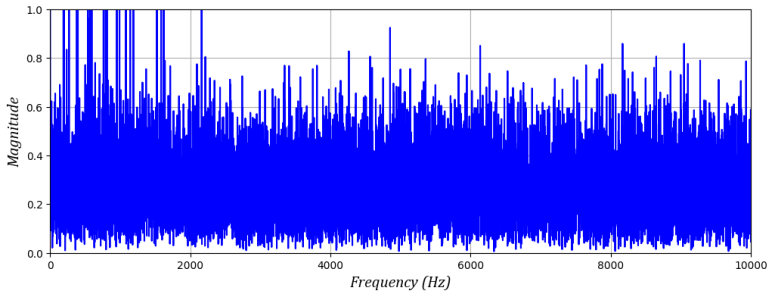


Figure 3. FFT of the simulated signal with bearing characteristic fault frequencies, with noise and without filtering.

The vibration signal was subjected to band-pass filtering (50–5000 Hz), followed by the Hilbert transform for envelope extraction Fig. 4. Next, Discrete Wavelet Transform (DWT) was applied, using db4 and Morlet wavelets for multiresolution decomposition [8]. The wavelet-level spectrograms revealed intensification in these bands over time. The acceleration envelope was implemented according to Johansson [9] using the Hilbert transform in a simplified convolution form:

$$H\big(f(t)\big) = \left(\frac{1}{\pi\, t} *\ f(t)\right). \tag{11}$$

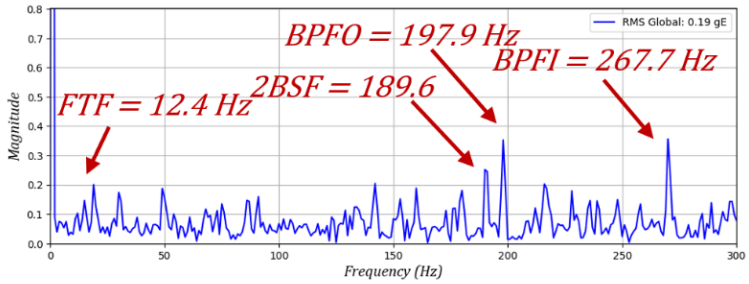


Figure 4. Envelope frequency spectrum from the Hilbert transform of the simulated signal with bearing characteristic fault frequencies.

The responses of the db4 and Morlet wavelets to the simulated signals were compared and both showed good selectivity in identifying localized impacts [10]. The Morlet-based DWT was selected for implementation and proved superior to conventional techniques in detecting transients at early fault stages as shown in Fig. 5 and 6 [11]. According to Polikar [10], wavelet transforms are organized into families derived from a "mother" wavelet, as follows:

$$f(t) = C_{\psi}^{-1} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{a^2} \langle f, \psi^{a,b} \rangle \, \psi^{a,b}(t) \, da \, db \, . \tag{12}$$

where a and b represent the wavelet scale (or level) and translation, respectively, where $a \neq 0$; $\psi^{a,b}(t) = |a|^{\frac{1}{2}} \psi\left(\frac{x-b}{a}\right)$ and $\langle \quad , \quad \rangle$ denotes the L^2 inner product. C_{ψ} is a normalization constant that depends on ψ.

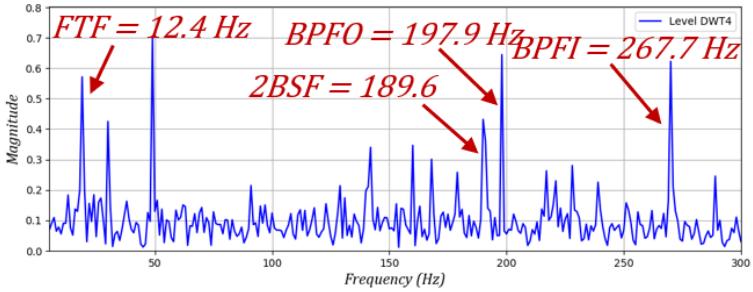


Figure 5. Envelope frequency spectrum of the 4th level Morlet wavelet of the simulated signal with bearing characteristic fault frequencies.

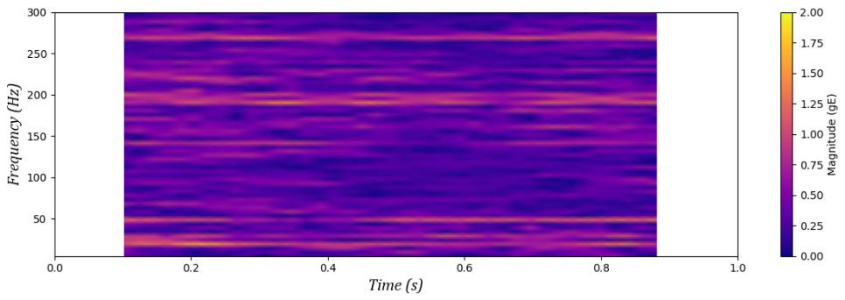


Figure 6. Spectrogram of the 4th level Morlet wavelet of the simulated signal with bearing characteristic fault frequencies.

3 Experimental Setup

The experiment was conducted with a NSK self-aligning ball bearing model 1207 K, mounted in a split housing SNAL 507-606, on a test bench shown in Figure 7. After one hour of operation under normal conditions,

abrasive particles were introduced into the lubricant to accelerate wear. Vibration data were collected in parallel using an accelerometer, following the specifications of ISO 20816-1 [6].



Figure 7. Bearing test bench with drive motor, torque motor, and pulley transmission system.

3.1 Experimental Analysis and Discussion

After contamination, a progressive increase in the global RMS levels was observed Fig. 8. By analyzing the wavelet decomposition levels, a vibration peak at the ball pass frequency of the outer raceway, close to 200 Hz, was detected Fig. 9.

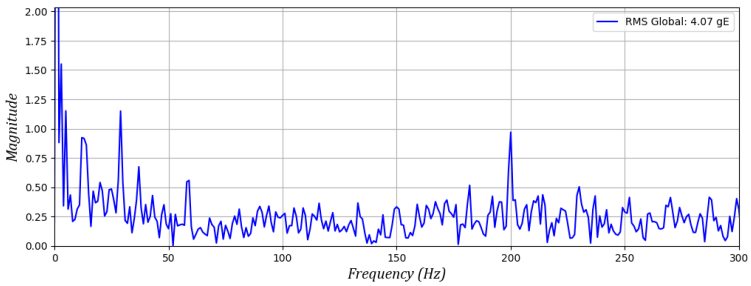


Figure 8. Envelope frequency spectrum from the Hilbert transform of the signal acquired from the bearing housing using an accelerometer.

The same spectral resolution advantage obtained with the simulated signal, shown in Figs. 6 and 7, can be observed in the real signal acquired from the bearing housing shown in Figs. 9 and 10, where noise was attenuated, enabling better identification of the onset of the defect in the bearing's outer race.

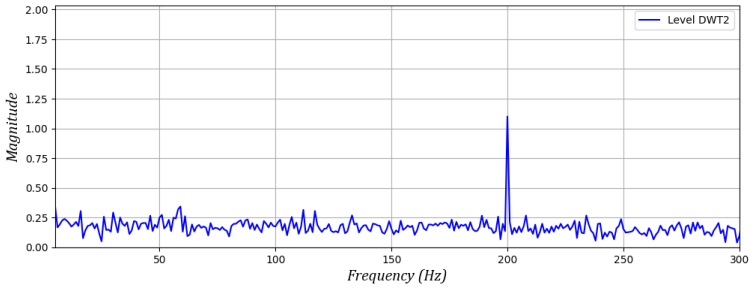


Figure 9. Frequency spectrum of the 2nd level Morlet wavelet of the signal acquired from the bearing housing with a peak at the BPFO frequency.

The spectrogram shown in Fig. 10 enables analysis in both the time and frequency domains, which facilitates the identification of transients, as occurs in bearing fault signals. This effect should have higher resolution for a signal with a longer acquisition time.

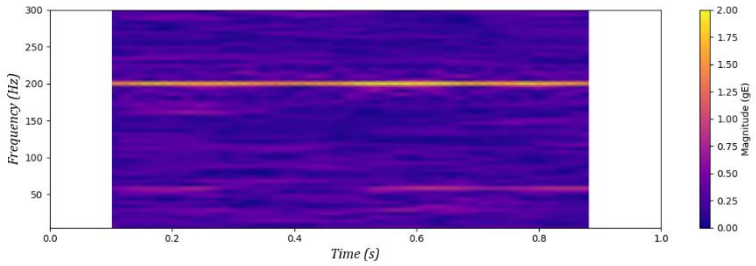


Figure 10. Spectrogram of the 2nd level Morlet wavelet of the signal acquired from the bearing, with a light-colored signature and a transient at the BPFO frequency.

4 Conclusion

This work has theoretically and experimentally demonstrated that the Wavelet Transform is an effective tool for the early diagnosis of faults in rolling-element bearings. Multiresolution decomposition, combined with pre-processing via band-pass filtering and envelope extraction using the Hilbert transform, increased selectivity to localized impacts and attenuated noise, making it possible to highlight signatures typical of incipient defects. In particular, intensified impacts were observed at the ball/roller pass frequency of the outer race (BPFO) at approximately 200 Hz. These results point to practical gains in predictive monitoring systems by reducing diagnostic uncertainty and anticipating maintenance interventions, with potential direct impact on the availability and reliability of rotating equipment. From an applied standpoint, the approach proved possible to integrate into industrial routines already based on envelope analysis and FFT, adding the time–frequency dimension needed for transient detection. Even so, the study's limitations are acknowledged: the experimental dataset considered a single bearing type (NSK 1207 K), a degradation mechanism induced by abrasive contamination, and a relatively short acquisition window.

As future avenues, one could consider expanding the operational envelope—load, rotational speed, and signal duration—and fusing vibration with other quantities such as temperature and electric current to make the diagnosis more robust. In addition, machine-learning classifiers can be employed for severity quantification and real-time decision-making, aligning the method with Industry 4.0 monitoring architectures. In short, the methodology presented consolidates a solid technical foundation for early and reliable bearing diagnostics, while also paving the way for its scalability and field automation.

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