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Embedded algorithm for the diagnosis of machine tool spindles

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Abstract

Spindle maintenance is a crucial process in the metal-cutting industry. If the spindle's operation is not adequately observed, it could lead to significant damage that increases exponentially with each use. Therefore, a spindle maintenance system is a top priority for any metal-cutting factory looking to enhance spindle performance while reducing overall operating costs. The most vulnerable part of the spindle is the bearing, which can fail due to factors such as a lack of lubrication, over-lubrication, contamination, overloading, excessive temperature, or misalignment. These issues can result in inner race fault (BPFI), outer race fault (BPFO), ball defect (BSF), or cage failure (FTF). Edge computing devices have emerged as a promising solution for reducing traffic load to the cloud and can be employed to monitor machine operation and diagnose spindle failures. In this article, we present an algorithm for diagnosing BPFI, BPFO, BSF, and FTF based on Kurtosis, Hilbert transform, and Wavelet Transform methods. The results demonstrate that the developed algorithms are accurate and computationally efficient, meeting the demands of edge devices.

Embedded algorithm, Edge device, Spindle, Bearing fault diagnosis

1. Introduction

Spindles play critical role in machining processes, offering rotational motion to cutting tools for precision and efficiency in manufacturing. Being crucial components of machine tools, their performance directly impacts machining quality. Ensuring spindle reliability requires focused maintenance, particularly in bearing fault detection and chatter detection.

Early fault identification is critical to prevent costly failures, minimize downtime, and ensure safety. By implementing effective bearing fault detection techniques, particularly vibration monitoring, potential issues can be identified in their early stages. The types of bearing faults include inner race fault (BPFI), outer race fault (BPFO), ball defect (BSF), or cage failure (FTF) and grease failure [1][2]. In comparison to ISO 17243 [3], our method has incorporated the signal enhance technique for better bearing fault detection.

Chatter refers to the unwanted vibration and oscillation that can occur during metal-cutting processes, leading to poor surface finish quality, accelerated tool wear, and, in extreme cases, catastrophic tool failure. Chatter detection is essential to prevent these detrimental effects and optimize the machining process. By employing advanced sensing technologies and real-time monitoring systems, manufacturers can promptly identify the presence of chatter and take corrective actions, such as adjusting cutting parameters or implementing damping techniques.

2. Bearing fault detection algorithm

To detect the ball bearing parameters, the Hilbert transform is employed. The Hilbert transform of the signal $x_H(t)$, is obtained through the convolution of the original signal $x(t)$ with $1/\pi t$. The crucial step in utilizing the Hilbert transform for bearing fault diagnosis involves acquiring the envelope of the analytic signal s(t). The envelope reflects variations in the amplitude of the signal over time, aiding in the identification of fault-related frequency components. The analytic signal is formed using the following formula, and the power spectral density of this analytic signal is capable of detecting bearing fault frequencies.

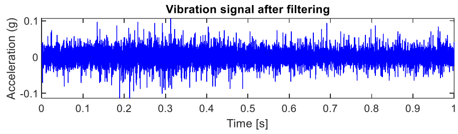
$$s(t) = x(t) + j\, x_H(t) \qquad (1)$$

There are alternative ways to address the noise problem in the signal, such as Kurtosis and wavelet transform, which are compared with experimental results. We gathered spindle vibration data and implemented the system for the bearing with the following configuration:

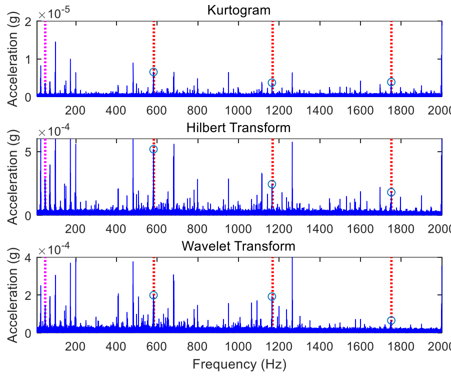
Table 1 Bearing configuration and its calculated fault frequencies (f_s, N_b, D_b, d_c, and α are spindle speed(Hz), # of ball, ball diameter, pitch diameter, and contact angle respectively):

	Theoretical Bearing fault frequency	**Bearing fault frequency**
BPFI	$f_s \frac{N_b}{2}\left(1 + \frac{D_b}{d_c} cos(\alpha)\right)$	$11.7076 \times f_s$
BPFO	$f_s \frac{N_b}{2}\left(1 - \frac{D_b}{d_c} cos(\alpha)\right)$	$9.2924 \times f_s$
FTF	$\frac{f_s}{2}\left(1 - \frac{D_b}{d_c} cos(\alpha)\right)$	$0.4425 \times f_s$
BSF	$f_s \frac{N_b}{2}\left(1 - \left(\frac{D_b}{d_c} cos(\alpha)\right)^2\right)$	$4.1438 \times f_s$

In Table 1, theoretical bearing fault frequencies such as BPFI, BPFO, BSF, and FTF coexist with the calculated bearing fault frequencies derived from the current spindle system. In Figure 1, raw data is captured from a spindle with an inner race fault, and the calculated BPFI is depicted using the three aforementioned algorithms. As investigation from experiment data, the BPFI and its harmonic 1x, 2x, 3x appear as 585.8 Hz, 1070.7 Hz, 1756.14 Hz in the frequency domain implying fault in the inner raceway (red lines in Fig. 1 (b)).



(a) Time domain signal



(b) Frequency domain transformed signals

Figure 1. BPFI fault signal in time and frequency domain

3. Chatter detection algorithm

Chatter refers to undesirable vibrations or oscillations that occur during machining, resulting in poor surface quality, tool wear, reduced machining efficiency, and potential damage to the workpiece, cutting tool, or the machine itself. Two methods for chatter detection include analyzing the power spectrum density (PSD) of the signal and employing the wavelet packet decomposition transform or stationary wavelet transform (SWT).

Each cutting condition is associated with the tool passing frequency, f_c. This frequency represents the integer multiplication of the spindle speed, i.e., the number of flutes on the tool. The vibration signal we collected consists of the periodic component $s_p(t)$, aperiodic component $s_a(t)$, and noise $s_n(t)$ as indicated with its indies a and p. In the scope of this noise is considered to be negligible. The PSD of the signal is calculated by:

$$PSD_{total} = PSD_a + PSD_p \quad (2)$$

The energy of aperiodic signal is

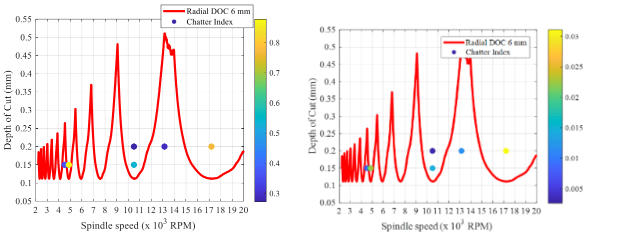
$$E_a = \sum_0^{N-1} PSD_a$$
$$E_p = \sum_0^{N-1} PSD_p$$
$$E = \sum_0^{N-1} PSD_{total} \quad (3)$$

The chatter index (CI) is calculated by the formula:

$$CI = E_a/E \quad (4)$$

The E_a is representative of the aperiodic signal, signifying that when the CI is large, i.e., close to the normalization value , there is the presence of unwanted signal. The PSD of the periodic signal is associated with vibrations generated from collisions between the tool flute and the workpiece. This periodic data occurs consistently, regardless of the presence of chatter. Therefore, this part is excluded from the PSD_{total} obtain the PSD of the aperiodic signal.[4]

The Chatter Index can also be determined using the wavelet transform, specifically the SWT, similar to the PSD method. This approach leverages the wavelet transform's ability to detect transient features in vibration signals, which are often signs of bearing faults. Unlike the PSD, the wavelet transform uniquely identifies various data frequencies over time, making it a good method for chatter detection. The calculation is based on the randomness of the wavelet coefficients, with higher randomness indicating a higher chance of chatter. This principle underlies our method for calculating the Chatter Index using the wavelet transform.



(a)CI from PSD (b) CI from SWT

Figure 2. Chatter index based on PSD and SWT (red line is SLD, dots indicate cutting condition, and are colored according to CI level)

Table 2 shows the cutting conditions and their Chatter Index (CI) using the SWT and PSD methods. Despite a cutting speed of 10500 rpm showing no clear chatter indicator, both methods effectively predict chatter, as shown in Figure 2's red line of stable lobe diagram (SLD). The dots are the cutting condition from experiment with spindle speed and depth of cut. Conditions below this line are stable, while those above are unstable.

Table 2 Cutting condition and the corresponding chatter index

ADOC (mm)	Speed (RPM)	CI (SWT)	CI (PSD)
0.15	4500	0.007	0.35
0.15	4785	0.015	0.39
0.15	4870	0.022	0.87
0.15	10500	0.0144	0.54
0.2	10500	0.0026	0.27
0.2	13140	0.0119	0.29
0.2	17200	0.0311	0.77

4. Conclusions

In this paper, we present an embedded algorithm for bearing fault detection and chatter detection, designed for application in embedded systems. A robust and easily calculable algorithm is essential for embedded systems. Therefore, the Hilbert transform and PSD approach are recommended for bearing fault and chatter detection due to their robustness and fast calculation. The choice of method depends on the operator's requirements. If there is no constraint on the edge calculation system, more complex methods like fast kurtosis for bearing fault detection and wavelet transform, along with SWT for chatter detection, are viable options. These methods offer a deeper analysis, but it is crucial to consider the trade-off between calculation time and performance.

References

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