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Cross-correlation of whitened vibration signals for low-speed bearing diagnostics

Andreas Klausen *, Kjell G. Robbersmyr

University of Agder, Department of Engineering Sciences, Jon Lilletunsvei 9, 4879 Grimstad, Norway

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ABSTRACT

Rolling-element bearings are crucial components in all rotating machinery, and their failure will initially degrade the machine performance, and later cause complete shutdown. The period between an initial crack and complete failure is short due to crack propagation. Therefore, early fault detection is important to avoid unexpected machine shutdown and to aid in maintenance scheduling. Bearing condition monitoring has been applied for several decades to detect incipient faults at an early stage. However, low-speed conditions pose a challenge for bearing fault diagnosis due to low fault impact energy. To reliably detect bearing faults at an early stage, a new method termed Whitened Cross-correlation Spectrum (WCCS) is proposed. The method computes the cross-correlation between the whitened vibration signal and its envelope. In this paper, it is detailed how this correlation can improve the fault diagnosis compared to analyzing the envelope spectrum alone. Compared to other methods reported in the literature, the WCCS provides accurate fault detection without involving experimentally tuned settings or bandpass-filtering. Vibration data at 20 rpm rotational speed from an accelerated life-time test of a 40 mm bore size bearing is used to verify the performance of the proposed method. An additional case study using the WCCS on a difficult dataset from the Case Western Reserve University database is also presented to verify the performance.

1. Introduction

Rolling-element bearings, or bearings for short, are crucial components in all rotating machinery. Their failure is one of the most common cause of machine breakdown. A worn bearing is characterized by increased vibration levels, internal looseness, and higher friction. The increase of vibration can damage nearby components, and lead to a full stop of the machine. If worn bearings are not replaced in time, costly downtime or personnel injuries may occur. Condition monitoring techniques can be applied to estimate the bearing health and remaining useful life-time. Data from sensors that measure a physical quantity, like the vibration, are used as input to such a system. The data is further analyzed using signal processing algorithms, before the results are presented to an operator. Based on the results, the operator can decide whether the bearing is in a healthy state, or if it is worn and should be replaced. Such condition monitoring systems have been used for several decades to monitor the health of all kinds of rotating machinery components. The most common sensor type to use is vibration accelerometers, as the bearing vibration is closely linked to the amount of internal wear. An incipient fault, on either bearing race-way or a roller, causes an impulse of vibration every time it is struck. The spectral frequency of the resulting

* Corresponding author.
E-mail address: andreas.klausen@uia.no (A. Klausen).

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Nomenclature

a	ARM parameters
AE	acoustic emission
AIC	Akaike Information Criterion
AIC_C	corrected Akaike Information Criterion
α	angular lag
a_{opt}	optimal ARM parameters
ARM	autoregressive Model
DRS	deterministic/random separator
$\Delta\theta_d$	desired shaft angle interval
E	kurtosis of white Gaussian noise
F	Fourier transform
f_{ot}	spline interpolation function
F_s	vibration data sampling rate
H	Hilbert transform
I_t	impulse train
j, k	indexes
μ_4	fourth central moment
n_h	number of bearing fault harmonics
N_r	vibration samples per revolution
n_r	number of shaft revolutions
$n_{s,j}$	number of side-bands linked to harmonic j
n_w	size of Hann window
O_{2BS}	$2\times$ ball spin orders
O_{bcf}	list of bearing characteristic fault orders
O_{BPI}	ball pass orders inner race
O_{BPO}	ball pass orders outer race
O_{FT}	fundamental train orders (cage speed)
O_S	shaft speed in orders
p	ARM order
P1, P2	performance metrics
ϕ	random phase
p_{max}	maximum ARM order
p_{opt}	optimal ARM order
ψ	ball bearing contact angle
rpm	revolutions per minute
SC	spectral Correlation
σ	standard deviation
SNR	signal-to-noise ratio
θ	shaft angle in No. of revolutions.
$\dot{\theta}_{(ref)}$	shaft speed reference
V	vibration data
V_a	analytic vibration signal
V_{as}	asynchronous vibration
V_{cc}	cross-correlated vibration signal
V_{env}	zero-mean vibration envelope
V_i	imaginary part of V_a
V_{ot}	order tracked vibration
V_s	shaft synchronous vibration
V_w	whitened vibration
W	white Gaussian noise
w	Hann window
WCCS	whitened cross-correlation spectrum
y	simulated signal for ARM filter example

vibration is based on the resonance frequency of the system and is normally in the thousands of Hertz. Further, the resonance frequency of a bearing system is normally not known as it is difficult to determine analytically or experimentally. However, the spectral frequency is not directly of interest when diagnosing a bearing. The cyclic frequency between each impact impulse may reveal its fault. By analyzing the kinematics of a bearing under no-slip conditions, the characteristic cyclic frequencies for the different fault types are determined. If the cyclic vibration frequency match any of the character-