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Circular domain features based condition monitoring for low speed slewing bearing

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ABSTRACT

This paper presents a novel application of circular domain features calculation based condition monitoring method for low rotational speed slewing bearing. The method employs data reduction process using piecewise aggregate approximation (PAA) to detect frequency alteration in the bearing signal when the fault occurs. From the processed data, circular domain features such as circular mean, circular variance, circular skewness and circular kurtosis are calculated and monitored. It is shown that the slight changes of bearing condition during operation can be identified more clearly in circular domain analysis compared to time domain analysis and other advanced signal processing methods such as wavelet decomposition and empirical mode decomposition (EMD) allowing the engineer to better schedule the maintenance work. Four circular domain features were shown to consistently and clearly identify the onset (initiation) of fault from the peak feature value which is not clearly observable in time domain features. The application of the method is demonstrated with simulated data, laboratory slewing bearing data and industrial bearing data from Coal Bridge Reclaimer used in a local steel mill.

1. Introduction

Slewing bearing is a subgroup of rolling element bearing commonly used in large industrial machineries such as turntable, steel mill cranes, offshore cranes, rotatable trolley, excavators, reclaimers, stackers, swing shovels, and ladle cars. They typically support high axial and high radial load. Slewing bearings are often critical production part. An unplanned downtime when a bearing breaks down can be very expensive due to the loss of production. Moreover as replacement of large slewing bearing can take several months to arrive due to long manufacturing and delivery time, plants often carry spare bearing to guard against these unforeseen circumstances adding an extra cost. In order to prevent unplanned downtime, a condition monitoring and prognosis method is needed.

Although there is no existing standard criterion for speed classification of rotating machinery, some published literatures mentioned that the rotating speed below than 600 rpm is categorized as low rotating speed machinery [1–3]. According to ISO 2372 which mentions that the classifications of vibration velocity severity covers machines with rotational speeds ranging from 600 to 1200 rpm and [4] mentioned that speed greater than 600 rpm is high speed machinery, thus in this paper the rolling bearing run at speed greater than 600 rpm is considered typical rolling bearing.

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Nomenclature

C	number of occurrence
d_m	mean bearing diameter
d_r	diameter of rolling element
EMD	empirical mode decomposition
FFT	fast Fourier transform
fs	sampling frequency
IMF	intrinsic mode function
ith	occurrence data point
IR_{rpm}	rotational speed of inner bearing ring
OR_{rpm}	rotational speed of outer bearing ring
k	circular kurtosis [11]
m	circular skewness [11]
N	number of data points of vibration signal
n	length of reduced-data, $n=N/w$
A_{RMS}	RMS of white noise amplitude
r	radius of circular plane
R	resultant vector length
S	number of samples for a half sinusoidal signal
$\mathbf{t}$	time vector, $\mathbf{t}=(t_1, t_2, \ldots, t_N)$
t_{max}	total time, $t_{max}=t_N$
V	circular variance
V_{RMS}	RMS of vibration signal amplitude
w	window size of PAA
$\mathbf{x}$	reduced data, $\mathbf{x}=(x_1, x_2, \ldots, x_n)$
$\mathbf{y}$	sampled vibration data, $\mathbf{y}=(y_1, y_2, \ldots, y_N)$
z	number of rolling elements
Z_i	circular plane of angular domain α_i
$\bar{Z}$	circular mean
$\boldsymbol{\alpha}$	the occurrence data set in circular domain, $\boldsymbol{\alpha}=(\alpha_1, \alpha_2, \ldots, \alpha_c)$
β	reversible angle of slewing bearing
γ	Lagrange multiplier
ϕ	shifting factor
λ	frequency that triggers the change of ellipsoid orientation

There have been extensive study of vibration analyses and features extractions for condition monitoring, fault diagnosis and prognosis of typical rolling bearing [5–8] and the results shown these techniques can effectively monitor the changes of bearing condition. In typical rolling bearing, once a fault is initiated the bearing can deteriorate rapidly within few hundreds/thousands revolutions and result in changes of vibration within very short time from the onset of the fault [8]. Thus in this case the use of features extraction methods such as time domain and frequency domain features calculation is effective to distinguish the bearing condition. However, the methods and features suitable for one directional typical rotating bearing cannot be applied effectively for identifying the abnormal condition of low rotational speed bearing [2] especially in extremely low rotational speed (≈ 1 rpm) slewing bearing [9]. This is due to the low impact energy emission from the rotating elements contact with a defect spot might not show an obvious change in vibration signature correspond to the bearing damage condition and thus become hardly detectable with conventional vibration analysis [10]. Moreover the bearing signal is also deeply masked by the background noise. Therefore, although time domain features [5–8] are extracted from the signal where the noise is dominant, the onset of bearing fault is still undetectable [9]. Eventually the amplitude is greater than the background noise, but by that stage features value will have increased substantially signifying that significant change of bearing condition has already occurred. Often by this stage the bearing condition is already close to unsustainable operation or near to failure.

To overcome the problem and prevent the sudden breakdown from occurring, alternative features which are able to identify the incipient fault is needed. This paper presents a novel application of circular domain features calculation based condition monitoring method for low rotational speed slewing bearing. In contrast to the previous angle and cyclic domain analysis discussed in Section 2, this paper employed circular analysis to extract the circular domain features. Circular analysis is a sub-class of statistic where it is different to general time domain statistical analysis. In circular analysis the statistical features such as mean, variance, skewness and kurtosis are calculated from the data distributed in circular domain or angular domain. Circular features were initially introduced in biological and medical science fields [11–13]. This paper combines piecewise aggregate approximation (PAA) data reduction process and circular features calculation (inspired by Berens [13]) as the monitored variables. The paper demonstrates the efficiency of the proposed method in detecting the onset of slewing reversible bearing fault. Reversible slewing bearing alternately rotates in clockwise rotation and anti-clockwise directions. The general steps of the proposed method are illustrated in Fig. 1. The method consist of three main steps: (i) reduction of the vibration data using PAA process and construction of neighborhood correlation plot of the reduced data, (ii) determination of the shape of the neighborhood correlation plot using ellipse least-square fitting for pattern classification and (iii) plot the distribution of the ellipse shape in angular domain, and calculation of the circular domain features (in the paper, bearing data between February and August 2007 was used as the test case). The detail description of Fig. 1 especially the signals output between the boxes from original vibration signal to ellipsoid pattern classification is presented in Section 4.6. The proposed method is compared to time domain features and advanced signal processing methods such as wavelet decomposition and empirical mode decomposition (EMD).

The paper is organized as follows: Section 2 reviews angular resampling method's application in rotating machinery; Section 3 presents the comparable advanced signal processing methods: the wavelet transform and the EMD method combined with statistical features; Section 4 discusses the theory and the merits of PAA method as slewing bearing signal processing tool, verification of PAA to identify frequency changes using simulated data, the application of PAA on vibration data, direct ellipse least-square fit classification, monitoring of faulty slewing bearing condition using PAA process, and detail signal processing flow process from original slewing bearing vibration signal to ellipsoid pattern classification; Section 5