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Bearing diagnostics using image processing methods

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ABSTRACT

In complex machines, the failure signs of an early bearing damage are weak compared to other sources of excitations (e.g. gears, shafts, rotors, etc.). The task of emphasizing the failure signs is complicated by the fact that changes in operating conditions influence vibrations sources and change the frequency and amplitude characteristics of the signal, making it non-stationary. As a result, a joint time-frequency representation is required. Previous vibration based diagnostic techniques focused on either the time domain or the frequency domain.

The proposed method suggests a different solution that applies image processing techniques to time-frequency or RPM-order representations (TFR) of the vibration signals in the orders-RPM domain.

In the first stage, TFRs of healthy machines are used to create a baseline. The TFRs can be obtained using various methods (Wigner-Ville, wavelets, STFT, etc).

In the next stage, the distance TFR between the inspected recording and the baseline is computed. In the third stage, the distance TFR is analyzed using ridge tracking and other image processing algorithms. In the fourth stage, the relations between the detected ridges are compared to the characteristic patterns of the bearing failure modes and the matching ridges are selected.

The different stages of analysis: baselines, distance TFR, ridges detection and selection, are illustrated with actual data of damaged bearings.

1. Introduction

Monitoring of vibrations can be used to detect machine faults, including: unbalance, misalignment, oil film bearing instabilities, roller bearing degradation, gearwheels degradation, eccentricity, mechanical looseness, structural resonance, and cracked rotors. In most cases, the detection is based on comparison of vibration levels at specific frequencies to reference or “baseline” values (representing the healthy cases).

Diagnostics of rotating machinery during regular operation involves in many cases analysis of non-stationary signals as the rotating speed, loads, and environmental conditions vary (in some cases rapidly) with time. Therefore, the algorithms should allow analysis of non-stationary or quasi-stationary signals.

Monitoring rotating components degradation (bearings, gears, rotors) by vibration analysis is a researched area and various methods of analysis have been previously published. The prevalent methods include frequency representations, orders representations, synchronous averaging, and enveloping [1–5,11,12,14]. Most of the condition indicators are based on the peak values or energies in the frequency spectrum, orders representations and envelope's spectrum.

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In a changing environment, where loads vary rapidly, the signals are non-stationary, and the assumption of quasi-stationarity is not appropriate. In such an environment, an efficient way to evaluate condition indicators may be based on time-frequency or time-order representations that reveal the evolution of the spectra with time. The time-frequency or time-order representations (TFR) can be calculated using different techniques of signal processing such as Short Time Fourier Transform (STFT), Wavelets decomposition or Wigner-Ville representations [6–10,13].

Usually the TFRs are representations of the vibration signal or its derivatives (synchronic average, envelope, pre-whitened signals, etc.) in the RPM-frequency or RPM-order domains.[1] TFRs are considered as basic tools in vibration analysis. They are widely used in scientific and industrial applications for visual inspection of vibrations. The primary problem is that for complex machinery, the TFR contains a huge amount of information and the expert is required to filter the relevant information manually. Sometimes this tedious process yields human errors.

The current paper proposes a fully automatic procedure for analysis of any kind of a three dimensional function (representation) and its application for automatic detection of faulty bearings. The analysis algorithm emphasizes the exceptions relative to the "baseline" or the reference TFR. The "baseline" is a statistical modeling of the TFRs derived from a set of healthy machines. The exceptions relative to the baseline are examined to detect patterns corresponding to faulty components, using image processing algorithms.

In the first section of the article, we will describe the statistical modeling stage, which is called baseline generation. Then we will show a procedure for emphasizing the exceptions in the analyzed TFR (relative to the baseline). Next, we will explain the algorithm for automatic detection and classification of patterns corresponding to bearing faults, and in the last section, we will discuss additional applications and conclusions.

The paper presents the stages of processing, i.e. baseline definition, distance TFR, ridge tracking, and finally the method proposed for determination of scores for bearing deterioration. It presents a method for analysis and extraction of condition indicators from TFRs. The method can be used both within an automatic diagnosis process or to facilitate an expert evaluation of the machine condition.

2. Baseline generation

The baseline is generated from TFRs collected from a set of healthy machines. In essence, the baseline is a statistical model of the data distribution in each cell of the TFR matrix:

$$\mu_{i,j} = \frac{1}{N}\sum_{n=1}^{N} P_{i,j,n} \quad \sigma_{i,j} = \frac{1}{N}\sqrt{\sum_{n=1}^{N} P_{i,j,n}^2} \tag{1}$$

where: $\mu_{i,j}$ is the average of values in cell i,j, $\sigma_{i,j}$ is the standard deviation of the values in cell i,j, N is the number of TFRs in the baseline, and $P_{i,j,n}$ is the value of the spectrum n in cell i,j.

In our application, where we used RPM-order spectrograms, a set of statistical parameters was calculated for each cell. The calculated parameters were the mean and the standard deviation, but any other set of statistical parameters can be calculated in the same manner.

It is highly advisable to use similar operating conditions for baseline generation. This allows higher detection capabilities and a better representation of the healthy population. To illustrate that, let us consider slow acceleration versus fast acceleration in a jet engine. In our experience, the two cases differ significantly in their vibration patterns even at the same RPM. Evidently, loads on bearings vary significantly, some of the resonances that are excited during a slow acceleration may not be present at a fast acceleration, and there are also differences in the amplitude of peaks at characteristic frequencies. Combining both cases of fast and slow accelerations into the same baseline model may lead to a significant reduction in discrimination abilities of the condition indicators.

Thus, it is essential to decide which operating conditions may be combined in the baseline. This can be achieved by a relatively simple statistical hypothesis testing procedure, combined with a physical understanding of the load variations in the different operating conditions.

Various technical issues should be addressed during the implementation of the baseline algorithm.

First, all the TFRs need to have the same scale. This can be achieved either by interpolation of the existing TFRs to a new common scale, or by calculation of the TFRs using a predefined common scale. The predefined common scale is achieved by calculating the TFRs at predefined ranges of rotating speeds and similar frequency/order resolution.

If interpolation is used, one should be careful not to introduce artifacts to the data when the time scale does not fit the variation rate of the load. For example, when the time resolution or RPM resolution is too low compared to the acceleration rate, and adjacent spectra differ abruptly in amplitude, the interpolated spectrum may generate an erroneous baseline TFR with high variances.

Another issue is how to set a correct scale. A higher resolution in time or RPM will provide better detection capabilities, but setting the resolution too high may leave some time segments of the TFR too short for a reliable spectrum calculation. The scale should be adapted to the operating modes of the inspected machinery so that most of the TFR will be calculated correctly.

[1] RPM – Rotations Per Minute.