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Towards automatic detection of local bearing defects in rotating machines[☆]

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Abstract

In this paper we derive and compare several different vibration analysis techniques for automatic detection of local defects in bearings.

Based on a signal model and a discussion on to what extent a good bearing monitoring method should trust it, we present several analysis tools for bearing condition monitoring and conclude that wavelets are especially well suited for this task. Then we describe a large-scale evaluation of several different automatic bearing monitoring methods using 103 laboratory and industrial environment test signals for which the true condition of the bearing is known from visual inspection. We describe the four best performing methods in detail (two wavelet-based, and two based on envelope and periodisation techniques). In our basic implementation, without using historical data or adapting the methods to (roughly) known machine or signal parameters, the four best methods had 9–13% error rate and are all good candidates for further fine-tuning and optimisation. Especially for the wavelet-based methods, there are several potentially performance improving additions, which we finally summarise into a guiding list of suggestion.

Keywords: Bearing; Condition monitoring; Vibration analysis; Signal model; Prediction; Classification; Wavelet; Morlet; Continuous wavelet transform; Wavelet packets; Matched filter; Envelope method; Periodisation

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1. Introduction

Bearing failures in rotating machines can cause both personal damages and economical loss. Manual inspections are not only expensive, but also connected with a risk of accidentally *causing* damages when reassembling a machine. Thus there is a clear need for non-destructive methods for predicting bearing damages early enough to wait with bearing replacements until next scheduled stop for machine maintenance. The most successful such methods in use today are all based on vibration analysis (see, e.g. [1,2]). They do, however, require special competence from the user, whereas, as the industry optimises there is less personnel and time available for condition monitoring. Thus important information to support decisions is lost and there is a demand for more automatised and supportive bearing monitoring software.

Classical bearing monitoring methods can usually be classified as either time domain methods (see, e.g. [3–6]) or frequency domain methods (see, e.g. [7–10]). These methods look for periodically occurring high-frequency transients, which however is complicated by the fact that this periodicity may be suppressed. Moreover, classical Fourier methods tend to average out transient vibrations (such as those typical for defect bearings), thus making them more prone to "drown" in the background noise of harmless vibrations. A natural countermove is to use methods that show how the frequency contents of the signal changes with time. This kind of analysis is usually referred to as time–frequency analysis. The *continuous wavelet transform* (CWT) is one such transform which is particularly good at separating the short high-frequency outbursts of a typical localised bearing defect from long-duration low-frequency signal components (occurring, for example, at multiples of the axis rotational frequency). Since its introduction in the mid-1980s the theory of wavelets has grown very rapidly in almost every field of signal processing and recently research has begun in areas of mechanical vibration analysis (see, e.g. [11–18]).

However, it is extremely important to point out that a new analysis technique only can provide more reliable diagnoses if the new mathematics and signal processing are combined with a deep insight into and experience of different types of rotating machinery.

This was the starting point of a unique Swedish joint research project with participation from Nåiden Teknik, the Centre of Applied Mathematics (CTM) at Luleå University of Technology, the Royal Institute of Technology (KTH) in Stockholm, the Swedish Institute of Applied Mathematics (ITM), and the three forestry combines AssiDomän, Modo and StoraEnso. This text is a condensed and rewritten version of selected parts of the final report [19] of that project.

The final goal is an automatic bearing monitoring system with easily interpreted output data that reflects the probability of a defect bearing (see Fig. 1).

We divide this analysis into three steps: First some analysis method is applied to an acceleration measurement $\mathbf{a}$ (here usually of length $N = 16,384$). The analysed signal $\mathbf{b}$ requires some expert knowledge for a correct interpretation. Depending on the analysis method, the length N' of $\mathbf{b}$ is usually comparable to N (or even N^2 for 2D-plots). This is too much for standard classification methods. Thus, as an intermediate step, we need to pick out the important information from $\mathbf{b}$ and reduce it to some n-dimensional $\mathbf{c}$ for a reasonably small n (e.g. $n = 2$ in plots like the one in Fig. 10(b)). Then a classification method can give the desired automatic diagnosis "functional" or "defect" (possibly with some additional judgment about the type and size of the defect):

$$\mathbf{a}\in\mathbb{R}^N \xrightarrow{\text{Analysis}} \mathbf{b}\in\mathbb{R}^{N'} \xrightarrow{\text{Reduce dimensionality}} \mathbf{c}\in\mathbb{R}^n \xrightarrow{\text{Classification}} \text{Diagnosis}.$$