Bearing diagnosis with the help of adaptive filters and wavelet de-noising techniques

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Introduction

At the very early stage of development of damage on bearings, the non-deterministic characteristic of its vibration signal requires alternative approaches in order to isolate and analyse the bearing signal. In one hand, the bearing signal comes from the rolling contact between races and rolling elements and do not present so much pronounced components related to the rolling frequency. On the other hand, additional noise sources on the machine contributes to its total vibration, usually measured on its housing, and consequently contaminating the useful signal.

To try to extract the useful bearing signal out of measured signal an algorithm using Adaptive Filtering and Wavelet-de-nosing technique [1] is used. The extra knowledge of the transfer functions of the machine [2] and of a physical model of the vibration produced by the bearing [3] gives additional information that can be used to feed the algorithm. This is a major difference in relation to traditional schemes where a reference signal (usually a specific signal pattern) is used to feed the de-noising algorithm. In the case presented, the simulation of the vibration of the bearing and the measured vibration of the machine are used to generate the machine's overall noise coming from other unwanted sources. This overall noise is then used to de-noise the signal of 5 other rolling bearings tested.

Both de-noised and simulated results for cylindrical and spherical rolling bearings on a running machine are compared and the results and limitations of the technique are discussed.

Modelling of the Bearing Vibration

The impossibility to measure the real excitation produced by the rough rolling contact between rolling elements and races in a bearing makes it necessary to model this mechanism.

The advantage of having this information is that it is now possible to predict what is the excitation produced by the bearing that is imposed to the machine, i.e., how this specific vibration source contributes to the overall vibration of the machine that is measured on its housing. Additionally, one can accompany the changes of this excitation with the degradation of the bearing. One must say that this contribution can only be evaluated if the influence of the machine itself as a medium is known. This is described in the next item.

The model starts from the measurement of the roughness of the rolling elements and the races. In very early stages of damage, when no material removal has yet occurred, the rough contact between the rolling partners and the races is the dominating source of vibration produced by the bearing and the signal generated by them is non-deterministic.

From the measured roughness profiles an equivalent one is constructed to represent the whole contact situation on the bearing. Assuming a quasi-stationary rolling process, one is able to calculate the displacements, velocities and accelerations to be imposed by the bearings to the machine.

The major advantage of this approach is to have a more exact description of the real actual situation of the surfaces of the bearing and to follow up their degradation [3].

Transfer Functions

The transfer function is an attempt to describe the influence of the machine itself (in form of damping or amplification over the frequency) over the signal imposed to it by the bearing. It was measured in a mounted machine (most near of real running situation) with the use of special designed actuators. These actuators were built from cylindrical and spherical rolling elements by adapting piezo ceramics on them. Through the application of a tension, a force signal could be generated by the actuator and captured by acceleration sensors positioned on the machine's housing. The measurements were repeated through 34 different positions of the rolling element on the bearing and for the two types of bearing, showing how the signal travels from different points to the sensors. In a running machine, the rough rolling contact of each rolling element contributes to the whole signal, but the transfer paths to the sensors are different and have to be taken into account. Additionally, the influence of the radial load was also measured. Although it is impossible to take into account all the dynamic effects of a running machine (the transfer function measurements have to be made in still stand), the results presented in [2] and [3] show a reasonable agreement between measured signals in running condition and the simulation of the vibration of the machine.

Adaptive Filtering

All surrounding structures in a machine, the dynamic effects and its dependence on temperature, lubrication, clearances etc. contribute to its actual vibration. In most of the cases, the useful signal for diagnosis is submerged in background noise, especially in early stages of failure development. That is why an efficient technique to extract useful signal from noisy measurements is of great importance.

The usual way to do such an estimation is to use a suitable filter that tends to suppress the noise while leaving the signal relatively unchanged. To do so, one has to have a reference signal (preferably totally uncorrelated with the signal wanted), and use this as pattern for the de-noising algorithm. This reference signal will be used to filter the measured signal (usually a mixture of wanted signal and background noise) to attenuate or eliminate by cancellation the noise in the last one. Computationally, it means the search of a unique solution that approximates a function (described by filter coefficients) that minimizes the quadratic mean error $MSE=E\{e[n]^2\}$ from the difference between the estimated

function and the reference signal. Here E{} denotes the statistical expectation operator and e[n] the error signal.
For signals with unknown statistical properties, fixed algorithms are not efficient. The adaptive algorithms however, change their characteristics by interactively modifying its internal parameters.
In this work an attempt with the Recursive Least-Square Algorithm (RLS) is tried. The main aim of this algorithm is to minimize the sum of the squares of the difference between the desired signal and the model filter output. On every interaction, new samples of the incoming signals are updated, so as the internal parameters. This is useful for time-varying processes and fits better the case in study. However, the use of recursive algorithms has the major drawback of increasing computational complexity as well as having some stability problems.

Wavelet de-noising

As far as the Wavelet is concerned, two main points are of major relevance. First, the decomposition of the signal through the Discrete Wavelet Transform that delivers coefficients describing weighting factors of a series of waves and that can be used to reconstruct the signal through an inverse transform. Second, the thresholding procedure that consists in eliminating (setting to zero) terms of the series whose coefficients are smaller of a certainly chosen threshold.
The main objective of the wavelet de-noising is to suppress the additive noise $N_1[n]$ of the measured signal $s[n]= x[n]+N_1[n]$, where the signal x[n] is the wanted bearing signal. The signal s[n] is decomposed in L-level of wavelet transform and the coefficients below the threshold are suppressed.
In order to work, an additional signal $N_2[n]$ is needed. In traditional applications, this signal should be non-correlated with x[n], but correlated with the noise $N_1[n]$. One should noticed that what is here called noise ($N_1[n]$) is the contribution of all other sources of vibration on the machine that are not the source wanted, in this case the bearing signal, and not what is classically understood by noise.

Results

A series of 3 spherical rolling bearings and 3 cylindrical rolling bearings were tested. The signals of the running bearings (720 RPM) were measured through 2 accelerometers under a radial load of 16 kN (except for cylinder bearing 1 with 32 kN). The transfer functions [2] and an appropriate model of contact [3] were also available.
Instead of the traditional approach, in this attempt, the spherical rolling bearing was used as reference. The de-noising algorithm was first fed with the measured signal of ball bearing 1 and the simulation of the excitation produced by this bearing. Assuming that the physical modelling of the excitation is a good approximation of the real signal produced by the bearing and regarding it now as the 'noise' that has to be extracted from the measurement, the result of the de-noising procedure should deliver the unwanted influence of the machine over the signal (unwanted background noise). If now, this unwanted background noise extracted from the measurements of ball bearing 1 (with the help of the simulated excitation) is used to de-noise the whole set of other bearings, one obtains signals that should approximate the real excitation imposed to the machine by the bearings.
Figures 1 and 2 below show the simulations and de-noised signals for the spherical and cylindrical rolling bearings.
It can be seen that the dominant frequencies are reproduced until around 10 kHz. Over this range, other effects present of the measured signals and that are not modelled, could cause the disparity between the results.

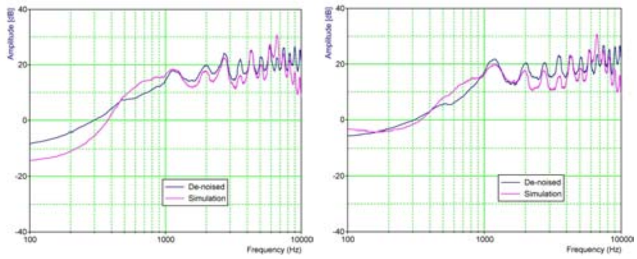

Figure 1: Simulation and de-noised signals from spherical rolling bearings 3 (left) and 4 (right). The noise extracted from spherical bearing 1 was used as reference to de-noise the measurements of the other bearings. Spherical bearing 2 was totally damaged and could not be simulated.

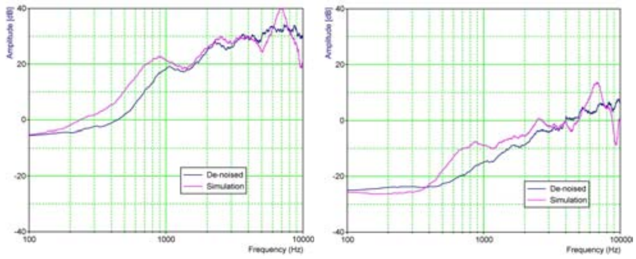

Figure 2: Simulation and de-noised results from cylindrical rolling bearing 1 (left) and 2 (right).

Conclusions

A procedure to de-noise machine signals to extract relevant bearing signals is showed in this paper. The procedure takes advantage of an existing model of the rough rolling contact in bearings [3] to feed in the de-noising algorithm with a reference information. The results show the feasibility of this approach and gives reasonable results below 10 kHz. The impossibility to model all possible sources of vibration as well as to predict the whole influence of other effects like the dynamic, temperature, clearances etc., makes it difficult to extract relevant signals that are submerged in unwanted noise. Further developments concern the improvement of the de-noising algorithm and the refinement of the reference signal.

Literature

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