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ANALYSIS OF ROLLING BEARINGS VIBRATION DURING NONDESTRUCTIVE TESTING ON GEARBOX

Adam Dočekal*[1], Marcel Kreidl[1], and Radislav Šmíd[1]

[1]Department of Measurement, Faculty of Electrical Engineering,
166 27 Prague 6, Czech Republic
docekaa@fel.cvut.cz

Abstract

This paper describes a case of vibroacoustic testing of a gearbox. Especially conditions of a rolling bearing in the gearbox were analyzed and monitored. The aim of this work was recognition and classification of different types of rolling bearings faults. This work is focused on spectral analysis used for feature extraction. There were compared different ways of power spectral estimation during various load conditions and various revolution rates. The described feature extraction took into account changes of energy of the vibration signal after reassembling the tested gearbox. A vibration signal of a rolling bearing described by its spectral amplitude features was classified by two simple common-known neural classifiers: Multilayer perceptron and Radial basis neural network.

INTRODUCTION

Rolling bearing conditions monitoring has received considerable attention for many years because the important part of problems in rotating machines is caused by faulty of rolling bearings. This paper basically describes rolling bearing inspection system shown in Fig. 1. There are basically two ways for rolling bearing monitoring: either the traditional time domain techniques inspecting overall vibration energy e.g. peak level, RMS value, and crest factor [1], or else spectral analysis which enables to estimate the source of vibration.

A number of frequency domain techniques has been developed which could be used to detect the fault, e.g. spectral, cepstral, and wavelet analysis. This paper was concerned on rolling bearing diagnostics using spectral analysis, rather using different spectrum estimation methods. Obtained condition indicators (features) were classified by two neural classifiers: Multilayer perceptron and Radial basis neural network.

The classical failure mode of rolling bearings is a localized defect. A piece of contact surface is dislodged in that case, mostly by fatigue cracking in the material during cyclic pressing. There are caused beats if a roller passes through this crack. This effect generally results in bursts of acoustic emission and sequentially in vibration. This takes effect in frequency spectrum of gearbox vibration by increase in corresponding frequencies. Defects at different locations of a bearing (inner race, roller and outer race) can be characterized by different own characteristic defect frequency. Assuming pure rolling contact and negligible elastic deformation of bearing component, characteristic defect frequencies can be calculated from the geometry and speed of a bearing using the equations (1) to (3) [1].

$$f_o = \frac{n}{2} f_r \left(1 - \frac{BD}{PD} \cos \beta \right) \tag{1}$$

$$f_i = \frac{n}{2} f_r \left(1 + \frac{BD}{PD} \cos \beta \right) \tag{2}$$

$$f_b = \frac{PD}{2BD} f_r \left(1 - \left(\frac{BD}{PD} \cos \beta \right)^2 \right) \tag{3}$$

where f_o, f_i and f_b are characteristic frequencies of outer race defect, inner race defect and defect on a ball or roller. BD is a roller diameter, PD is a bearing pitch diameter, f_r is rotating speed, β is a contact angle between race and ball, n is a number of rollers.

Figure 1 – Inspection system

So characteristic defect frequencies specified by shown equations make it possible to detect the presence of a defect and diagnose in what part of bearing the defect appears, but there may be concluded that there are localized defects on the outer race of bearing if there can be seen a frequency occurring at race close to theoretical estimation of the characteristic defect frequency for corresponding defects on the outer race.

FEATURE EXTRACTION USING SPECTRAL ANALYSIS

Feature extraction procedure is one of important parts of signal processing for condition monitoring. An efficient representation (description) of a bearing condition using a suitable basis should be used in order to reduce the dimensionality of the feature vectors characterizing the bearing state and make a state description containing all considerable information which can be further processed in the classifier.

Different spectra estimation methods were employed and discussed for feature extraction in this paper: Power Spectral Density (PSD) estimation by periodogram [2], PSD estimation by Welch's method, PSD estimation by AR model, and MUSIC spectrum estimation. The Welch's method splits a set of data into smaller sets of data and calculates the modified periodogram (the power spectrum) of each set [2]. AR model and MUSIC estimator will be described consequently.

As wear progresses (see eq. (1) to (3)), the fault becomes repetitive and ultimately related to running speed e.g. also as higher harmonics. Defect frequencies may also appear as a modulation on a high frequency signal. Because of bearing vibration being related to revolution speed of the shaft, there could be useful to assess the level and frequency of revolution speed vibration as the reference level. In practice, many bearing components contain natural frequencies almost in the range up to 2000 Hz, and thus the analysis could be focused on this bandwidth to reduce influence of high-frequency signal respective noise on used spectral density estimation method, e.g. AR model or MUSIC spectrum estimator.

There could be evaluated entire shape of spectrum (or PSD) or only bandwidths round corresponding characteristic defect frequencies can be evaluated. The spectrum shape evaluation may afford higher sensitivity because of higher harmonic of bearing vibration signal, but there has to be considered that the energy and distribution of vibration, consequently spectrum shape, may change after reassembling the tested machine.

AR Model

Conventional methods, based on Discrete Fourier Transform (DFT), are pretty capable to represent correct shape of spectrum or PSD truly, but DFT based methods don't provide stable PSD estimation for a non-stationary signal. Furthermore, they don't often allow achieving necessary resolution at frequency. That is why there were developed other methods for power spectra estimation. Described AR estimation of PSD is one kind of these methods.

Power spectral density modeling by AR (Auto-Regressive) model is based on approximation that power spectral density of analyzed signal by square of the frequency response magnitude of the matching filter [2]. This procedure so called spectral matching is described in eq. (4).

$$S_x(f) = \frac{T \cdot P_e}{\left|\mathbf{A}(f)\right|^2}, \tag{4}$$

where $S_x(f)$ is the estimated power spectral density, T is a sample period, P_e is a constant which matches power of signal spectra to the model, and $\boldsymbol{A}(f)$ is a frequency response of matching filter.

AR model estimates the PSD of an input signal vector using the Yule-Walker method. This method fits autoregressive linear filter model to the signal by minimizing the forward prediction error (based on all observations of the input sequence) in the least squares sense. The obtained spectral estimation is the squared magnitude of the frequency response of this AR model. Because the method characterizes the input data using an all-pole model, the correct choice of the model is important. The choice should correspond to your signal (similar to an assumed number of peaks).

MUSIC Estimator

The MUSIC (MUltiple SIgnal Classification) algorithm estimates the spectrum from a signal or a correlation matrix using Schmidt's eigenspace analysis method [3]. The method split the input signal space into signal subspace and noise subspace. The algorithm performs eigenspace analysis of the signal's correlation matrix in order to estimate the signal's frequency content. This algorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise. The MUSIC spectrum estimation $Px(f)$ is given by eq. 5.

$$P_x(f) = \frac{1}{\sum_{k=p+1}^{N} \left|\mathbf{v}_k^H \mathbf{e}(f)\right|^2}, \tag{5}$$

where N is the dimension of the eigenvectors and $\boldsymbol{v}_k$ is the k-th eigenvector of the correlation matrix. The integer p is the dimension of the signal subspace, so the eigenvectors $\boldsymbol{v}_k$ used in the sum correspond to the smallest eigenvalues and also span the noise subspace. The vector $\boldsymbol{e}(f)$ consists of complex exponentials, so the inner product amounts to a Fourier transform. This is used for computation of the spectrum estimate. The FFT is computed for each $\boldsymbol{v_k}$ and then the squared magnitudes are summed. In practice, the autocorrelation matrix is not known and must be often estimated from the measured data samples.

CLASSIFICATION BY NEURAL NETWORKS

Bearing condition state was evaluated and classified using neural networks classifiers. There was used supervised teaching for this purpose. The features of a bearing condition were classified by two neural classifiers: Multilayer perceptron and Radial basis neural network.

Multilayer perceptron

The neural network consists of a number of neurons interconnected via weights, which are iteratively tuned for a desired behavior of the network [4]. This class of networks consists of multiple layers of perceptron neurons, usually interconnected in a feed-forward way. The multiplayer perceptron (MLP) networks belong to the standard neural networks tools. Almost always, however, they are used for supervised learning, to the extent that often MLP networks are thought to be suitable only for supervised learning. MLP networks partition feature space with a combination of hyper-planes.

Radial basis neural network

The Radial basis neural networks (RBFNN) [4] are powerful techniques for classification in multidimensional space. RBFNN is a feedforward neural network with at least one layer of neurons using RBF functions. A RBF is a Gaussian-like transfer function, which has built into a distance criterion with respect to a center. Radial basis functions have been applied in the area of neural networks where they may be used as a replacement for the sigmoidal hidden layer transfer function in multilayer perceptrons. RBFNN decision boundaries are hyper-ellipsoids. Radial basis networks tend to have more neurons than standard feedforward networks.

EXPERIMENTS

Data acquisition

This was verified using measurements published in Data Bearing Center [5]. This website provides access to ball bearing test data for normal and faulty bearings. The test stand consists of a 1.5 kW motor, a torque transducer/encoder, a dynamometer. Single point faults were introduced to the test bearings using electro-discharge machining with fault diameters of 0.35 mm, 0.53 mm, 0.71 mm, and 1.02 mm. SKF bearings were used for this experiments. Vibration data was collected using accelerometers, which were attached to the housing with magnetic bases. During some experiments, an accelerometer was attached to the motor supporting base plate as well. Vibration signals were collected using a 16 channel DAT recorder. Speed and load value were collected using the torque transducer/encoder. Faulted bearings were reinstalled into the test motor and vibration data was recorded for motor loads of 0 to 2 kW (motor speeds of 1797 to 1720 RPM).

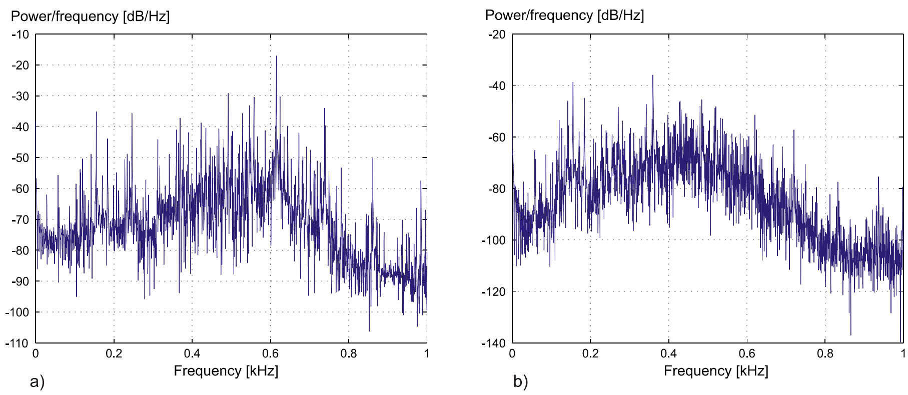

Figure 2 – Power Spectral Density estimate via Periodogram
(a - bearing without any fault ,b – bearing with fault of diameter at 0.53 mm at the inner ring)

The acceleration data used in this paper was measured at locations near to the motor bearings and was collected at 12,000 samples per second. Only faults introduced separately at the inner raceway and outer raceway were evaluated in this research.

Feature extraction using spectrum estimation

Bandwidths at 50 Hz round corresponding characteristic defect frequencies for inner race and for outer race were evaluated for feature extraction in this work. A condition feature was formed by a mean value of spectrum within this bandwidth. Signal was filtered by low-pass Butterworth filter with stop-band frequency at 700 Hz to ensure right condition estimating.

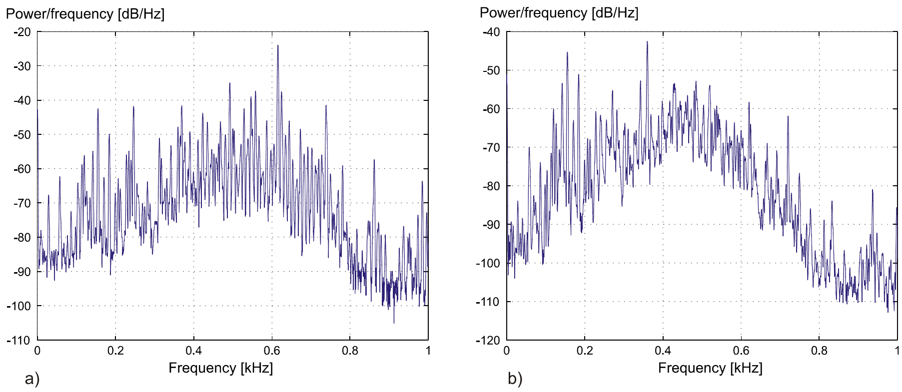

Figure 3 – Power Spectral Density estimate via Welch
(a - bearing without any fault ,b – bearing with fault of diameter at 0.53 mm at the inner ring)

Different spectral estimation for one kind of bearing fault are shown in figures 2 to 5. The revolution speed was 29.5 Hz, and estimated inner ring characteristic defect frequency was 146 Hz. The order of used AR model was 56. The order of MUSIC was 30. The length of a DFT window was 512 for both.

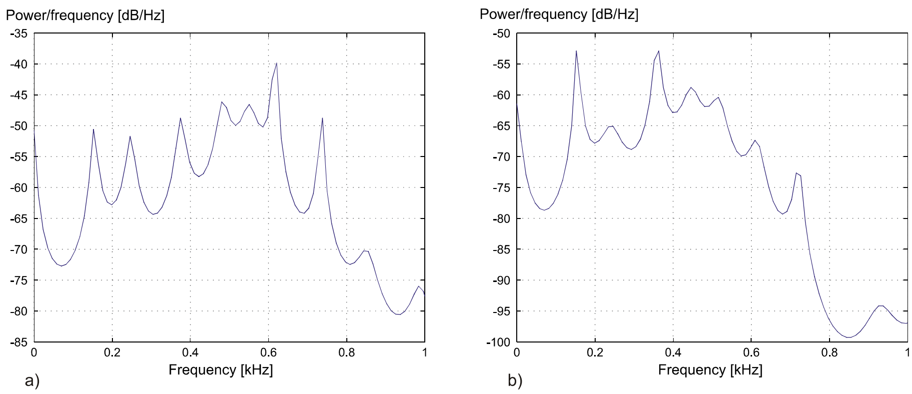

Figure 4 – Power Spectral Density estimate via AR model
(a - bearing without any fault ,b – bearing with fault of diameter at 0.53 mm at the inner ring)

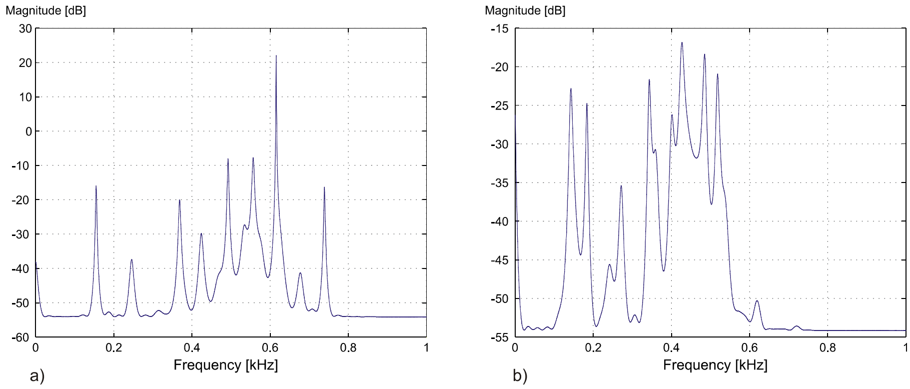

Figure 5 – Pseudospectrum estimate via MUSIC
(a - bearing without any fault ,b – bearing with fault of diameter at 0.53 mm at the inner ring)

Classification

A set containing 152 records was classified. A set contains 9 classes: four kinds of faults for inner and outer race, and records of bearing without faults. There were used 30 % randomly selected records of the set for training the classifiers. The record was measured with different load and revolution speed of the shaft.

A network with one hidden layer containing 7 neurons was used. The network was trained using the backpropagation learning rule with the Levenberg-Marquardt algorithm. This algorithm appears to be the one of the fastest methods for training this kind of networks. For multiclass classification, there was used one binary coded output per class. For a given output, the associated class corresponds to the index of the maximum value in the output vector.

We use a network with one hidden radial basis layer. The number of neurons in the hidden layer was 10. K-means algorithm was used for training the RBF network.

Because of there was different number of vectors in classes, whereas the smallest class contained only 8 records, efficiency of classification was evaluated by summarizing wrong classifications through the simulation part of the set. Comparison of efficiency of classification by multi-layer perceptron neural network for different ways of spectrum estimation is shown in table 1.

Table 1 – Efficiency of classification via different spectra estimations

Estimation	*Wrong classifications* [%]
Periodogram	3.7
Welch	2.8
AR model	2.8
MUSIC	1.9

CONCLUSION

A bearing condition monitoring technique based on spectral analysis of monitored bearing vibration was investigated. This paper has outlined in greater detail the different analysis techniques based on estimating the spectrum of the bearing vibration. Vibration of the tested bearings was evaluated by two neural classifiers. Classification was able to recognize different bearing conditions, but there was not enough bearing vibration data to perform statistic evaluation of classification results. AR model and especially MUSIC spectrum estimation performed very well in this application. These vibration spectrum estimation methods seem to be good alternative to wavelet analysis.

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