

## Vibration based diagnostic of cracks in hybrid ball bearings

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**Abstract** - The paper presents a vibration based diagnostic system to detect cracks in balls of hybrid ball bearings. The diagnostic system based on a Bayesian Classifier. It is shown that it is able to separate healthy bearings from damaged balls and races. The system is tested with measurement data from a bearing test bench in different operating points of the bearing.

### 1. Introduction

Diagnose wearing parts of machines and engines improve the availability, safety and help to reduce material usage. The diagnosis of bearings can be used for predictive maintenance or to prevent worse damages in mechanical systems after a defect in the bearing was detected. Hybrid ball bearing implies that a ball bearing consists of ceramic balls between metal races. The advantages are lower friction, less weight of balls, higher bearing stiffness, and reduced heat generation. That means, through hybrid bearing higher rotation speed with the same loss of energy can be reached.

In aerospace application, it is important to design more efficient turbines and to reduce consequently fuel consumption and air pollution. A diagnosis of bearings is needed to increase the safety and to reduce the costs for maintenance by better scheduling.

In production and by mounting, it can not be excluded that there are tiny cracks on surface and subsurface of the balls. These can grow and if they are big enough it breaks out. If there is a break-out from surface of the balls it will damage in short time the races because of the high difference in hardness.

For common oil lubricated metal bearings in aircraft is a magnetic chip detector mounted in the oil flow to count the metal flakes. In the case of hybrid bearings, this method only indicates wear on metal races and not at ceramic balls. Dempsey et. al [1] show an approach to detect ceramic and metal debris in oil flow with a capacitance sensor and an optical particle counter. They can detect debris greater than 4  $\mu\text{m}$ . The disadvantage of an oil debris analysis is that it only detect a damage if material breaks out.

The aim of this article is to show how to diagnose ceramic balls with a tiny break out or only with a crack. The sooner the detection of ball defects the lower a damage progress in the races is. To avoid a fast damage progress on races occurred by defect balls, a vibration based diagnostic

system is recommended. For metal bearings, a vibration based damage detection is well-known. Many authors researched on this topic with various signal processing techniques since decades, for example [2, 3, 4, 5, 6, 7]. The focus in literature is the detection of break outs above 0.5 mm diameter.

### 2. Methodology for diagnosis

#### A. Features for diagnosis

To recognize damages successfully the choice of features are crucial. In order to detect them, the amplitude of bearing defect frequencies and their harmonics are important. For the most common ball bearings, it can be calculated with the following in literature well-known equations [8, 3, 7, 4] for the outer ring Eq.(1), the inner ring Eq.(2) and the balls Eq.(3).

$$f_o = \frac{n}{2} f_s \left( 1 - \frac{d_B}{d_P} \cos \beta \right) \quad (1)$$

$$f_i = \frac{n}{2} f_s \left( 1 + \frac{d_B}{d_P} \cos \beta \right) \quad (2)$$

$$f_b = \frac{d_P}{d_B} f_s \left( 1 - \left( \frac{d_B}{d_P} \right)^2 \cos^2 \beta \right) \quad (3)$$

With the ball diameter  $b_D$ , the pitch diameter  $d_P$ , the shaft speed  $f_S$ , the contact angle  $\beta$  and the number of balls  $n$ .

The amplitudes of defect frequencies were extracted from the envelope spectrum [9] of the vibration signal. The envelope spectrum is calculated by Hilbert transformation [5, 7].

Further features are the first six statistic moments (mean, variance, skewness, kurtosis [2]), the maximum peak-to-peak value and the crest factor of the vibration signal. The crest factor is the ratio between maximum value and the RMS-value. These features are calculated for different frequency bands.

All features shape the feature vector  $\underline{x}$ . The features have different values range so it is important to normalize them.

The features have to be rate for separability. This can be done with the trace criterion. First, the within-class scatter

matrix  $\underline{W}$  is needed. It is the mean covariance matrix of all classes.

$$\underline{W} = \frac{1}{K-1} \sum_{i=1}^K \left( E \left\{ \left( \underline{x}_i - \underline{\mu}_i \right) \cdot \left( \underline{x}_i - \underline{\mu}_i \right)^T \right\} \right) \quad (4)$$

The between-class scatter matrix  $\underline{B}$  is the covariance of mean values.

$$\underline{B} = E \left\{ \left( \underline{\mu} - \frac{1}{K} \sum_{i=1}^K \underline{\mu}_i \right) \cdot \left( \underline{\mu} - \frac{1}{K} \sum_{i=1}^K \underline{\mu}_i \right)^T \right\} \quad (5)$$

If the mean values of classes have a large distance and the spread of class means is small, then the features are well separable. The trace of a scatter matrix is the sum of variances.

$$J = \frac{Tr(\underline{B})}{Tr(\underline{W})} \quad (6)$$

To classify damages correctly, it needs to reduce the features. To avoid false diagnosis and to reduce computing time it is useful to use only features which improve the diagnostic results. The add-on algorithm is used to choose the right features:

1. Find a single feature with best classification result.
2. Find another feature combined with the first gives a better result.
3. Find further features combined with the previous which improve the result.

### B. Bayesian Classifier

The Bayesian Classifier [10] is based on the Bayes' theorem. The classifier assigns every pattern to the class with the highest likelihood. A pattern with the corresponding feature vector  $\underline{x}$  is one point in feature space.

$$P(C_i | \underline{x}) = \frac{p(\underline{x} | C_i) \cdot P(C_i)}{p(\underline{x})} \quad (7)$$

The a-posteriori-probability  $P(C_i | \underline{x})$  is the probability of class  $C_i$  for a given pattern  $\underline{x}$ .

A-priori-probability  $P(C_i)$  means probability for class  $C_i$ , in diagnostic case the probability for a specific damage or the probability for a fault free system.

The Likelihood function  $p(\underline{x} | C_i)$  of class  $C_i$  with respect to  $\underline{x}$  means how probably a given pattern  $\underline{x}$  is member of class  $C_i$ .

The likelihood function  $p(\underline{x})$  of the pattern. It is the sum of the class respected likelihoods  $p(\underline{x} | C_i)$  scaled with the a-priori-probability  $P(C_i)$ .

$$p(\underline{x}) = \sum_{i=1}^K P(C_i) \cdot p(\underline{x} | C_i) \quad (8)$$

The likelihood function  $p(\underline{x} | C_i)$  defines an area for each class in feature space. A pattern  $\underline{x}$  is a member of class  $C_i$  if it is in the defined area.

Hence the decision rule is:

$$\begin{aligned} &x \in C_i, \text{ if:} \\ &p(\underline{x} | C_i) \cdot P(C_i) > p(\underline{x} | C_j) \cdot P(C_j) \quad (9) \\ &\text{for } i \neq j \end{aligned}$$

In most real applications the class respected likelihood of the pattern  $p(\underline{x} | C_i)$  is unknown and has to estimate. The kernel density estimation is used here [10]. The estimation is realized by summarizing scaled density functions, the kernel functions.

$$\hat{p}(x) = \frac{1}{nh} \sum_{i=1}^n \phi \left( \frac{x - x_i}{h} \right) \quad (10)$$

with the kernel  $\phi(\cdot)$  and the bandwidth  $h$ .

A Gaussian kernel is used:

$$\phi(u) = \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{1}{2} u^2 \right) \quad (11)$$

### 3. Experiment

An angular contact ball bearing with ceramic ( $Si_3N_4$ ) balls is used for the tests. The bearing parameters are shown in Table 1.

Table 1. Test bearing parameters

parameters	value
number of balls	16
contact angle	15°
ball diameter	9.5 mm
shaft diameter	100 mm
pitch diameter	125 mm

The balls are damaged with crack and spalls. A crack is generated with an indenter ceramic ball. It pushes on the test ball with increasing force till an acoustic sensor detects an initial crack. The initial crack is in the crystal structure and can not be seen at the surface. From this point, the force will be increased to a defined offset depend on the desired crack length [11]. This method is similar to the standardized Brinell and Rockwell hardness tests. These cracks can emerge during ball manufacturing or bearing mounting. The cracks are called C-cracks because of their shape. A crack has only a width of some  $\mu\text{m}$ . Three different arc length up to 8 mm are available.

Three different spall sizes are generated. A laser drills holes up to 1 mm. A 1 mm hole is inside the ring. During the tests, rotation speed and load are varied. The parameters are shown in Table 2. The holes were generated to investigate the damage mode of a break-out.

At the test bench rotation speed and acceleration is measured. The acceleration are measured by an accelerometer from Kistler Type 8702B25 with an acceleration range of 25 g and a resonant frequency of 54 kHz mounted at the locking device and a raw Piezo-Element sensor mounted at the outer race of the bearing. All signals

Table 2. Testbench Parameter

Parameter	min.	max.
rotation speed, [1/min]	100	1800
axial load, [N]	0	2000
radial load, [N]	0	1800

from sensors are sampled with a DAQ-System from National Instruments at a sample rate of 200 kHz and a resolution of 16 bit.

#### 4. Results

The three different cracks sizes and the three different spall sizes were used for classifying. Also an undamaged bearing, one with an outer race damage and one with an inner race damage. For each class between 18 and 57 test runs were done, see Table 3.

Table 3. Measurements

kind	number of measurements
crack 3.7 mm	28
crack 4.7 mm	26
crack 7.9 mm	18
spall 0.4 mm	35
spall 0.7 mm	29
spall 1.0 mm	42
inner race	28
outer race	28

The quality of classifier output will be calculated by the rate of recognition from the test runs. Cross validation with leaving-one-out method was used:

1. Train the classifier with  $N - 1$  pattern.
2. Test it with the remaining pattern.
3. Repeat this procedure  $N$  times. Train each time with another pattern.

The classifier was trained to detect different crack and spall sizes. As well as in a second step to detect different damages in the bearing like inner, outer race and ball damage. The results are shown in Table 4.

Table 4. Test results

Test	detection rate in %
cracks – fault free	100
spalls – fault free	100
inner race, outer race, spalls, fault free	98,100,100,96

To simplify the multi class diagnosis problem to a two resp. three class problem following scheme is used Fig.1.

The first step is to detect a damage. In further steps, a more clearly diagnosis will be done. Which part of the bearing has a defect and how large is the damage? This method

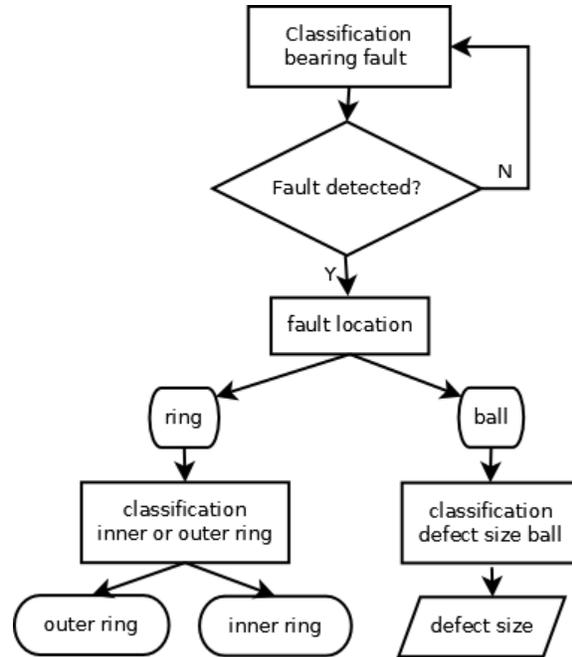


Figure 1. diagnostic scheme

has the advantage that for every detection problem a separate feature vector can be generated. On this way, all patterns could correct classified without wrong classification.

#### 5. Conclusion

It was shown that a classification system based on vibration sensors and together with a Bayesian Classifier can detect cracks and break-outs in hybrid ball bearings. This works for different working points of the bearing. The system can detect several kinds and sizes of ball damages as well as damages at the races. This works with accelerometers and also with raw Piezo-Element sensors. The result is improved with the implementing of a multi-stage classification.

#### 6. Acknowledgement

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detects damages and the failure progress velocity in hybrid ball bearing.

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