Bearing Damage Detection using Support Vector Machine

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Abstract. Vibration can be used for preventive condition monitoring in industrial equipment. Vibration measurement may avoid unexpected damages. The measurement data can be analyzed either by using signal processing or machine learning. This work assessed bearing damage detection as bearing is intensively used in industrial mechanical equipment. The assessment was performed experimentally by developing system prototype and measurement tools, including the use of laser vibrometer and a labjack as well as support vector machine to predict some types of damages. The work has been able to predict the BPFI, BPFO, BSF, and FTF damages by 93.125% accuracy. However, accuracy plunged to 61.25% when bearing damages were of three types: BPFO, BSF and FTF.

1. Introduction
An ideal engine should not exert vibration as the mechanical energy should be converted into work. Vibrations show the system imperfection that wasted the energy. Vibration is emerged as a cyclic force of mismatch elements that potentially deforming the surface and breaking the engine. One of ways to detect potential damaging sources is by detecting vibration as part of predictive maintenance [1].

Fast Fourier Transform (FFT) is generally used for extracting vibration signals. Ameid et al [2] used FFT to detect rotor imbalance that produces vibration. The generated spectrum enables imbalance detection as the source of vibration. FFT has also been used for detecting bearing damage [3]. FFT signal analysis was combined with Wigner-Ville distribution and modified poincare mapping to locate bearing failure.

The use of sophisticated sensors such as ultrasonic, eddy current, piezoelectric and strain gage sensors enable live monitoring on the engine vibrations. Some signal processing methods are available to extract signal features to define what happens to the mechanical devices. Further, practical classifier of machine learning can be used for differentiating between damages and goods. Damages were able detected by comparing features of extracted FFT spectrum.

Since failure diagnostic is an important part of condition monitoring to prevent un-predictive failure, the accurate method is still challenging to explore. The progress on machine learning is helpful to be implemented in this matter. Support vector machine (SVM) is the excellent pattern recognition system that is able to analyze features from bulk data in either time or frequency domain. The SVM performances are mainly depending on the feature extraction [4].

Several techniques have been proposed to enhance SVM performance in classifying vibration information. Intrinsic mode function (IMF) for spectrum enveloping has been proposed to find failure spectral line of decomposed modulated signal by using empirical mode decomposition (EMD). The amplitude and frequency of the failure characteristics were then used for SVM input. SVM classifier decided the engine status [5]. Other researcher used IMF envelope sample entropy (SampEn) to diagnose bearing problems [6]. The EMD extract vibration data adaptively into some IMFs. IMFs were sorted and envelops were used to find failure information. The envelop sample entropy (SampEn) prepares features for SVM input.
Bearing is an important device in industrial equipment. The broken bearing may result the damages on equipment. Local damage in bearing results scratch or holes in inner race (ball pass frequency inner race, BPFI), outer race (ball pass frequency outer race, BPFO), damage in rolling element (ball spin frequency, BSF) or cage damage (fundamental train frequency, FTF) [7]. Those damages should be detected before affecting the overall equipment.

Considering the aforementioned methods, there are two important components for vibration detection to reveal damages: vibration detection and spectrum extraction. Spectrum extractions either by using FFT, signal processing or machine learning are depending to the vibration detection. Since many sensors have been available to detect vibration, this paper proposes laser sensor and machine learning combination to detect vibration and to extract vibration data to determine bearing damages. The proposed method was examined by developing a mechanical prototype, setting up sensors and applying support vector machine.

2. Experiment design
The bearing evaluated in this paper is NTN UCP 204 D1, with specifications plotted in Table 1. Bearings were tested under conditions of new and damage. The bearings were examined for rotation speed of 400 to 1200 rpm, outer race damage, inner race damage, rolling element damage, and cage damage.

| No | Item                        | Size     |
|----|-----------------------------|----------|
| 1  | Number of balls (Nb)        | 8        |
| 2  | Diameter (Bd)               | 7.94 mm  |
| 3  | Pitch Diameter (Pd)         | 33.48 mm |
| 4  | Contact angle (α)           | 0        |
| 5  | Relative frequency (Fr)     | 23 Hz    |

The observed system was a prototype as shown in Figure 1. Table was made from metal with size of 500x500x500 mm, two poles with diameter of 20 mm and length of 300 mm and 500 mm were placed on table top. Four units of pillow block NTN UCP 204 were employed with mild steel holders; two spur gears of 33 and 2.5 were attached to the poles. Two 60 mm type-A V-pulleys and a V-belt A39 connects the mechanics to a 3-phase, 1380 rpm, 0.75 kW LM-Motor, which was supplied by 1 HP 3 phase inverter.

![Figure 1. The mechanical prototype](image)

The bearing assessment set up is shown in Figure 2. Bearings were assessed with speeds and poles axis varied. Vibration was read by using a laser vibration photo sensor, interfaced to a computer by using a labjack that converts analog measurement signals into digital form readable for computer. The vibrometer was located 376 mm from bearing. The laser was pointed horizontally, vertically and axial. Data were taken for various bearing conditions for speed of 400, 600, 800, 1000, and 1200 rpm. The extracted features covered mean, median, modus, root mean square, standard deviation, skewness, kurtosis, and beta kurtosis.
3. Assessment results
Vibration measurements were performed in base tread, base plat and in bearings. Vibrations in four base treads and base plats have low number of harmonics. Vibration in bearing is much larger than the two other places. Figure 3 shown time domain vibration sample for broken bearing that reach amplitude up to 26 µm.

![Broken bearing vibrations](image_url)
From the measured data, mean as the average value of data was calculated by using Equation 1. The root mean square was using Equation 2.

\[
\mu_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij} \quad (1)
\]

\[
RMS = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x^2(i)} \quad (2)
\]

Skewness \((y)\) as the symmetric value around samples was calculated by using Equation 3. The sharpness of data distribution \((\text{kurtosis}, K)\) and the forth moment of beta function \((\text{beta kurtosis}, BK)\) were using Equation 4 and 5.

\[
y = \frac{E(x-\mu)^3}{\sigma^3} \quad (3)
\]

\[
K = \frac{M_4}{\sigma^4} \quad (4)
\]

\[
BK = \frac{m_4}{(\sigma^4)} \quad (5)
\]

In addition to the aforementioned features, additional vibration differentials were added. Displacement was calculated by using Equation 6 and acceleration used Equation 7. Velocity was obtained from measurement, while the angle speed \((\omega)\) was calculated based on rpm \((n)\) (Equation 8).

\[
X = \int \dot{X}(t) = A \sin \omega t \quad (6)
\]

\[
\ddot{X} = \frac{dX}{dt} \quad (7)
\]

\[
\omega = 2\pi n / 60 \quad (8)
\]

The horizontal, vertical and axial vibrations generated by new bearings as in Figure 4 were made as training data for the support vector machine. The new bearing shows steady vibration with maximum amplitude of 3.2 µm.

(a) Horizontal amplitude  (b) Vertical amplitude  (c) Axial amplitude

**Figure 4.** New bearing vibrations
The SVM was used to determine either bearing is new or broken. The predicted damages include the BPFI, BPFO, BSF and FTF. Figure 5 shows SVM accuracy in predicting the condition of bearing. The average accuracy is 93.125%. The lowest accuracy occurred when bearing experiences three types of damages. Bearing 5 has damages of BPFO, BSF and FTF, so that SVM predicted less accurate, only 61.25%.

![Figure 5. SVM prediction](image1)

![Figure 6. Bearing condition](image2)

The SVM performed best when predicting the new bearings as the features were likely uniform. SVM gained 97.78% accuracy. The broken bearing was rather difficult to predict as the positions of scratches or holes can be minor or major. It reached 6.65% lower accuracy, about 91.13% as shown in Figure 6.

4. Conclusions
This paper has discussed the use of laser vibrometer and SVM to detect damages on bearings: BPFI, BPFO, BSF, and FTF. Vibrometer along with labjack is able to detect vibration in order of µm through horizontal, vertical and axial direction of vibrations. SVM produces in average 93.125% accuracy. The lowest accuracy occurred when there were multiple types of damages. In order to enhance prediction, characteristics combination of damage types should be explored and new features should be added into classifier.

References
[1] Jung D, Zhang Z, and Winslett M. 2017. Vibration analysis for iot enabled predictive maintenance. In IEEE 33rd International Conference on Data Engineering (ICDE) 1271-1282
[2] Ameid T, Menacer A., Talhaoui H, and Harzelli I. 2017. Broken rotor bar fault diagnosis using fast Fourier transform applied to field-oriented control induction machine: simulation and experimental study. The International Journal of Advanced Manufacturing Technology, 92(1-4), 917-928.
[3] Singru P, Krishnakumar V, Natarajan D, and Raizada A. 2018. Bearing failure prediction using Wigner-Ville distribution, modified Poincare mapping and fast Fourier transform. Journal of Vibroengineering, 20(1), 127-137.
[4] Fuqing Y. 2011. Failure diagnostics using support vector machine (Doctoral dissertation, Luleå tekniska universitet).
[5] Suresh S, and Naidu V P S. 2019. Vibration Analysis of Heterogeneous Gearbox Faults using EMD Features and SVM Classifier. In IOP Conference Series: Materials Science and Engineering, 624 (1), 012032. IOP Publishing.
[6] Xie Z Q, Sun H E, Liu L, and Wu C. 2017. Fault Diagnosis of Rolling Bearing Based on CEEMDAN Sample Entropy and SVM. Modular Machine Tool & Automatic Manufacturing Technique, 3 (25).

[7] Chen Y, Peng G, Xie C, Zhang W, Li C, and Liu S. 2018. ACDIN: Bridging the gap between artificial and real bearing damages for bearing fault diagnosis. Neurocomputing, 294, 61-71.