

Vibro-acoustic signal analysis for lubrication regime identification in rolling element bearings using local mean decomposition

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Abstract. Rolling element bearings are the essential mechanical elements of rotating machines, whose operation is basically controlled by the existing lubrication conditions. In the current paper, a new vibro-acoustic signal-based model of detecting lubrication regimes in rolling element bearings based on Local Mean Decomposition (LMD) with statistical feature extraction and machine learning classification is introduced. Experimental data were obtained in a SKF NJ 307 ECP cylindrical roller bearing that is running at 800 rpm with a radial load of 2.1 kN, and in various lubrication conditions including boundary, mixed and hydrodynamic conditions. An accelerometer was attached to the bearing housing to sample the vibration signals at 20 kHz and an acoustic signal sampler was attached to a calibrated microphone at 40 kHz inside a semi-anechoic chamber. LMD was used to break down the acquired signals into Product Functions (PFs) based on which time-domain statistical measures such as Root Mean Square (RMS), kurtosis, crest factor, and entropy have been derived. The experimental findings demonstrate that the boundary lubrication generates impulsive and high-kurtosis signals, whereby the energy is concentrated on high-frequency PFs, whereas hydrodynamic lubrication is characterized by smooth and lower-kurtosis signals with the energy concentrated at lower frequencies. Acoustic signals were more sensitive to lubrication transitions than vibration signals and inter-class feature separability was better. The Support Vector Machine (SVM) and the Random Forest classifiers trained using LMD-derived features were able to discriminate between the three lubrication regimes. The suggested methodology provides a powerful non-invasive system of real-time lubrication conditions monitoring and predictive maintenance of bearing systems.

Introduction

Rolling element bearings are invaluable elements in industrial rotating machines, such as electric motors, turbines, compressors, and machine tools. Their stable functioning is a precondition of the total system functioning, and the sudden failure of these systems might cause expensive unplanned downtimes and safety risks. Inadequate lubrication leads to bearing failure in about 43 percent of all bearing failures, improper mounting, (29 percent), deficient sealing, (18 percent), surface fatigue, (8 percent), and miscellaneous causes (2 percent) are among the leading causes of bearing failure [1]. This provides a significant rationale to the importance of well-developed methodologies which will be able to properly describe and measure the lubrication condition of bearings in operation.

The Stribeck curve is used to characterize the lubrication condition in a rolling element contact, and is characterized by three tribological regimes, namely: boundary lubrication (BL), mixed lubrication (ML), and full-film (elastohydrodynamic or hydrodynamic) lubrication (EHL/HL).



These regimes are measured by the specific film thickness parameter λ which is considered to be the quotient of lubricant film thickness to the roughness of the surface of the contacting bodies. At λ less than 1 the contact is boundary lubricated with high levels of asperity interaction and metal-to-metal contact leading to high levels of friction and wear. Mixed lubrication exists between 1 0 3, which is the partial film condition, and full film lubrication (0 3) that allows the surfaces to be completely separated by the lubricant film [2]. The change of these regimes has significant impacts on the vibration signature and acoustic emission properties of the bearing, which is the reason to drive signal-based diagnostic methods.

Traditional bearing condition monitoring techniques have been more organized to identify localized surface defects (e.g., outer race spalling, inner race pitting, rolling element cracking) and not to describe the underlying lubrication regime that causes defects [3]. Fast Fourier Transform (FFT)-based vibration analysis is the most commonly deployed technique in industrial practice, but the FFT-based approach has weaknesses in its capacity to analyse non-stationary and nonlinear signals that are typical of bearings that are subjected to time-varying lubrication conditions [4]. This has been a constraint that has promoted the sophisticated signal processing techniques that can be able to capture transient and multiscale dynamics of bearing vibro-acoustic responses. The first run-to-failure experiments of roller bearings were combined the explicit film thickness analysis with the Stribeck curve to describe the transition of lubrication regimes and their association with the grease degradation and surface fatigue wear [5]. Their study [6] later expanded on the impact of certain film thickness correction factors on the evolution of surface fatigue wear and the vibration signatures associated with them, showing that lubrication regime change is associated with characteristic shifts in vibration amplitude and spectral content. These investigations formed a conceptual basis of lubricant conscious bearing diagnostics.

The development of acoustic emission (AE) sensing has become a very sensitive alternative to the traditional accelerator-based vibration measurement as an indicator of bearing diagnostics. Ghamdi et al. [7] established that AE sensors are good diagnostic sources than vibration sensors in fault detection in roller bearings, especially when the defect is at an early stage of development. The more frequent frequency of AE (100 kHz-1 MHz) enables detection of the sub-surface stress wave activity related to asperity contacts before macroscopic damage is visible. Tandon et al. [8] also compared sound and vibration measurements in the detection of bearing defects finding that acoustic signals can be useful to detect outer race defects but that defects in inner race and rolling element were better detected using more sophisticated processing at lower speeds. J. Hansen, et al. [9] examined the characteristics of surface topography parameters that can regulate the lubrication and vibration properties and demonstrated that the skewness and average roughness of the surface play a prominent role in determining the friction coefficient in the various lubrication regimes. F. Sadeghi, et al. [10] established correlations between signal-based regime identification and variation of friction coefficient on the Stribeck curve, which provides a tribological foundation to signal-based regime identification. T. Williams, et al. [11] found that the wear severity on the inner race surface is the most strongly correlated with RMS vibration signals, and statistical vibration parameters can be used to monitor the surface roughness evolution during run-to-failure experiments.

M.M. Maru et al. [12] examined the influence of lubricant contamination, particle size, and concentration on vibration levels in healthy and defective bearings with the help of statistical parameters and frequency spectrum analysis, and found that the amplitude of vibration was strongly dependent on the size of the particle in the contaminants. As Karacay and Aktuk [13] showed, statistical parameters with spectral analysis can be used to diagnose the severity of defects in ball bearings during run-to-failure tests, with faults developing preferentially on the inside race in the conditions of the test. B.P. Clarke et al. [14] studied the bearing operating conditions in terms of sound signal analysis in terms of the bearing design parameters such as radial clearance,

roller number and the lubricant viscosity. The process of grease degradation is a significant precursor to the lubrication failure and J. Ren, et al. [15] demonstrated that lubricating grease is rather quickly degraded in EHL contacts due to the high shear rate and shear stress that cause changes in the film thickness and leads to the transition of the contact to the boundary lubrication. In line with this, P.M. Cann, et al. [16] applied Fourier Transform Infrared (FTIR) spectroscopy and X-ray diffraction to characterize products of grease degradation in run-to-failure bearing tests and found the formation of carbonyl bands due to base oil and thickener oxidation to be a good degradation indicator. These improvements notwithstanding, there remains a research gap: the majority of the studies independently implements one of the condition monitoring modalities (vibration or acoustic emission) and aims at a local defect detection instead of classifying the lubrication regime proactively [3,17]. In addition, the majority of experimental studies are based on the artificial defects introduction (through electric discharge machining or acid etching) instead of naturally developed run-to-failure situations [3]. Multi-sensor vibro-acoustic fusion with sophisticated adaptive signal decomposition approaches to the classification of lubrication regime is underutilized.

Empirical Mode Decomposition (EMD) has been used on bearing diagnostics to overcome the non-stationarity constraint of FFT but EMD suffers mode mixing, end effects, and sensitivity to noise which reduce fidelity of decomposition [18,19]. Local Mean Decomposition (LMD) by Smith [20] addresses most of these shortcomings through an iterative decomposition process of a signal into Product Functions (PFs) which are intrinsic amplitude- and frequency-modulated components [21]. The superior physical interpretability and decomposition accuracy of nonlinear vibration signals LMD has been shown to have over EMD makes it an ideal tool to describe the complex dynamics of bearings in different lubrication conditions. In order to fill the above research gaps, this paper introduces a multi-sensor vibro-acoustic signal acquisition, LMD-based adaptive signal decomposition, statistical feature extraction of PF components, and supervised machine learning classification as an effective way to accurately identify the lubrication regimes in the rolling element bearings. The experimental campaign involves use of run-to-failure bearing test rig that runs under realistic non-accelerated conditions using SKF NJ 307 ECP cylindrical roller bearing to ensure that the results obtained are practical. The contributions of this work are as follows: (i) systematic description of the vibro-acoustic signal signatures in the boundary, mixed, and hydrodynamic lubrication regimes; (ii) the use of LMD to extract multi-scale features in bearing vibro-acoustic signals; (iii) comparison of acoustic and vibration signal sensitivity to lubrication transitions quantitatively; and (iv) a machine learning pipeline to automatically

Experimental setup

Vibro-acoustic signals were obtained in controlled lubrication conditions by means of a purpose-designed rolling element bearing test SKF NJ 307 ECP cylindrical roller bearing bearing with a test bearing that was stalled with a constant load of 800 rpm and a radial loading of 2.1 kN was stalled at the hydraulic loading system. The experimental set-up is shown in Fig.1.

The accelerometer (MMF KS7800) was placed on the bearing housing in the Z-direction (radial load direction) and the vibration data were sampled at a frequency of 20 kHz. Concurrently, acoustic (sound) signals were recorded with a calibrated microphone (Bswa Tech) in a semi-anechoic chamber at 40 kHz, which minimized contamination by background noise. The temperature of the bearing was continually monitored with a K-type thermocouple and the surface roughness was measured periodically with a Pertometer profilometer and a Talysurf CLI 1000 (Taylor-Hobson) surface texture analyzer. All the data were measured through a DEWEsoft 8-channel data acquisition system.

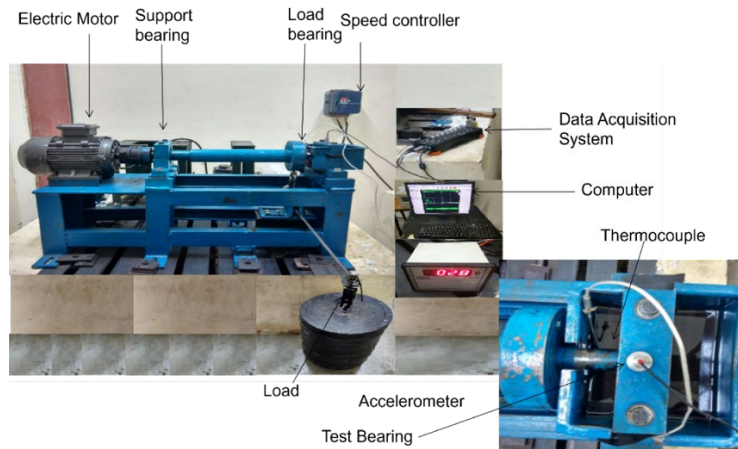


Fig.1. Experimental Set-up

The experimental procedure included a 100-hour run-in period with fresh grease, and subsequently, grease was changed. Regularly taken vibration and sound signals were then obtained at 100 hours intervals. The bearing was disassembled after every 300 hours of operation to measure the surface roughness and sample grease, a small amount of degraded grease was removed and an equal amount of fresh grease was added. The bearing test rig was run throughout 8 hours at a time and this gave thermal equilibrium.

Four lubrication conditions were also experimentally achieved, which are different steps of grease degradation and surface roughness development: (i) New/Healthy condition (fresh grease, smooth surfaces); (ii) Hydrodynamic lubrication (HL, $\lambda \approx 0.4$, full film regime); (iii) Mixed lubrication (ML, $\lambda \approx 0.6$); and (iv) B The Dowson-Higginson equation of film thickness was solved to obtain the specific film thickness λ as represented by the Dowson-Higginson film thickness equation as given in ensuing section, and was experimentally verified by measurement of periodic surface roughness.

Methodology

Lubrication Regime Characterization

The minimum lubricant film thickness $h_{\min}$ for the cylindrical roller bearing was computed using the Dowson-Higginson equation as modified by Pan and Hamrock [2]:

$$h_{\min} = 3.63 U^{0.68} G^{0.49} W^{-0.073} (1 - e^{-0.68k}) \cdot R_x \quad (1)$$

where U is the dimensionless speed parameter, G is the dimensionless material parameter, W is the dimensionless load parameter, and k is the ellipticity ratio. The specific film thickness λ is then defined as:

$$\lambda = h_{\min} / \sqrt{(R_{2q1}^2 + R_{2q2}^2)} \quad (2)$$

where R_{2q1} and R_{2q2} are the RMS surface roughness values of the roller and raceway surfaces, respectively. The λ values computed under the experimental operating conditions confirmed the classification into boundary ($\lambda \approx 1.0$), mixed ($\lambda \approx 0.6$), and hydrodynamic ($\lambda \approx 0.4$) lubrication regimes.

Signal Preprocessing

The raw vibration and acoustic signals were subjected to bandpass filtering to remove low-frequency shaft harmonics and high-frequency electromagnetic noise as shown in Fig.2. Signals were segmented into non-overlapping windows of 4096 samples (0.2 s at 20 kHz for vibration; 0.1 s at 40 kHz for sound) to ensure stationarity within each analysis frame. Five independent signal

segments were acquired per lubrication condition, yielding a total of 20 vibration and 20 acoustic signal records for analysis.

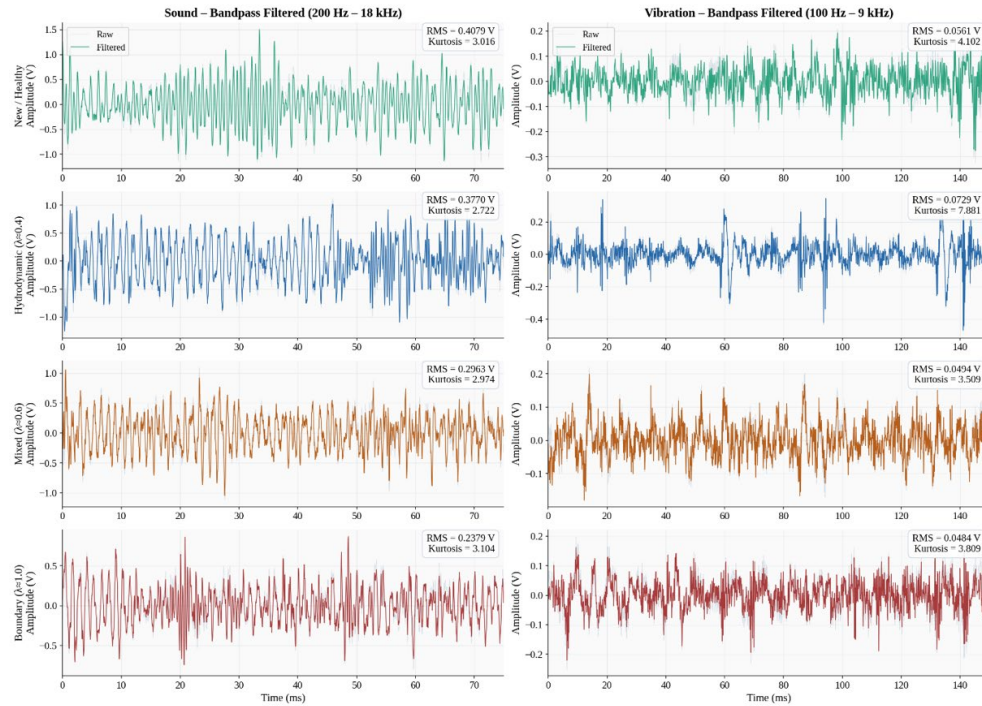


Fig.2. Bandpass filtering

Time and Frequency Domain Analysis

Statistical parameters were extracted from each signal segment in the time domain. The key metrics computed are defined as follows:

$$\text{RMS} = \sqrt{(1/N \sum x_i^2)} \quad (3)$$

$$\text{Kurtosis (K)} = (1/N \sum (x_i - \mu)^4) / \sigma^4 \quad (4)$$

$$\text{Crest Factor (CF)} = x_{\text{peak}} / x_{\text{RMS}} \quad (5)$$

where N is the number of samples, x_i is the i -th signal sample, μ is the signal mean, and σ is the standard deviation. Frequency domain analysis was performed using the Fast Fourier Transform (FFT) to identify dominant spectral components and bearing characteristic fault frequencies including Ball Pass Frequency Outer Race (BPFO), Ball Pass Frequency Inner Race (BPFI), Ball Spin Frequency (BSF), and Fundamental Train Frequency (FTF).

Machine Learning Classification

The extracted feature vectors were used to train and evaluate two supervised classification models: Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel and Random Forest (RF) classifier. A 70-30 stratified train-test split was applied, with 5-fold cross-validation on the training set for hyperparameter optimization. Class labels corresponded to the four lubrication states: New/Healthy, Hydrodynamic, Mixed, and Boundary. Classification performance was evaluated using accuracy, precision, recall, and F1-score metrics.

Results and Discussion

The calculated film thickness (λ) determined the change of full hydrodynamic ($\lambda > 3$) to mixed ($\lambda \approx 0.6$) and boundary lubrication ($\lambda \approx 1.0$) with the help of the observed surface degradation. Time-domain data shown in Table 1 indicated that acoustic RMS reduces steadily with lubrication degradation, but vibration RMS is non-monotonic. The maximum kurtosis of vibration (~ 6.96)

and crest factor, which are high periodic impulses, was generated by hydrodynamic lubrication, and less impulsive responses were generated due to boundary lubrication. LMD decomposition showed that the signal energy was redistributed among Product Functions (PFs) as the signal energy was predominantly distributed in the high-frequency regime (PF1) in healthy conditions, but in degraded lubrication, the signal energy was mainly concentrated in the mid-frequency regime (PF2-PF3). PF-level kurtosis substantiated enhanced impulsivity during boundary conditions and robust periodic excitation during hydrodynamic lubrication, which improved the separability of features. The acoustic and vibrations signals had complementary behaviour: acoustic signals had more distinct monotonic tendencies (RMS-based) whereas the vibration signal had more pronounced impulsive characteristics (kurtosis-based) and were more discriminative to classification. The results of classification proved that SVM with vibration LMD features are most accurate (94.4%), then comes Random Forest (88.9%), and acoustic-based models perform worse. Mixed lubrication had the lowest classification accuracy because it was transitional. All in all, the vibration-based LMD features are more capable of classification and acoustic features can make it more sensitive to lubrication degradation.

Table 1. Statistical parameters of vibro-acoustic signals across lubrication regimes.

Lubrication Condition	Sound RMS (V)	Sound Kurtosis	Sound CF	Vibration RMS (V)	Vibration Kurtosis	Vibration CF
New / Healthy	0.412	3.027	3.44	0.064	3.676	5.05
Hydrodynamic ($\lambda\approx0.4$)	0.382	3.495	4.67	0.074	6.955	6.43
Mixed ($\lambda\approx0.6$)	0.297	3.026	3.79	0.052	3.530	4.18
Boundary ($\lambda\approx1.0$)	0.252	2.840	3.37	0.064	3.056	3.93

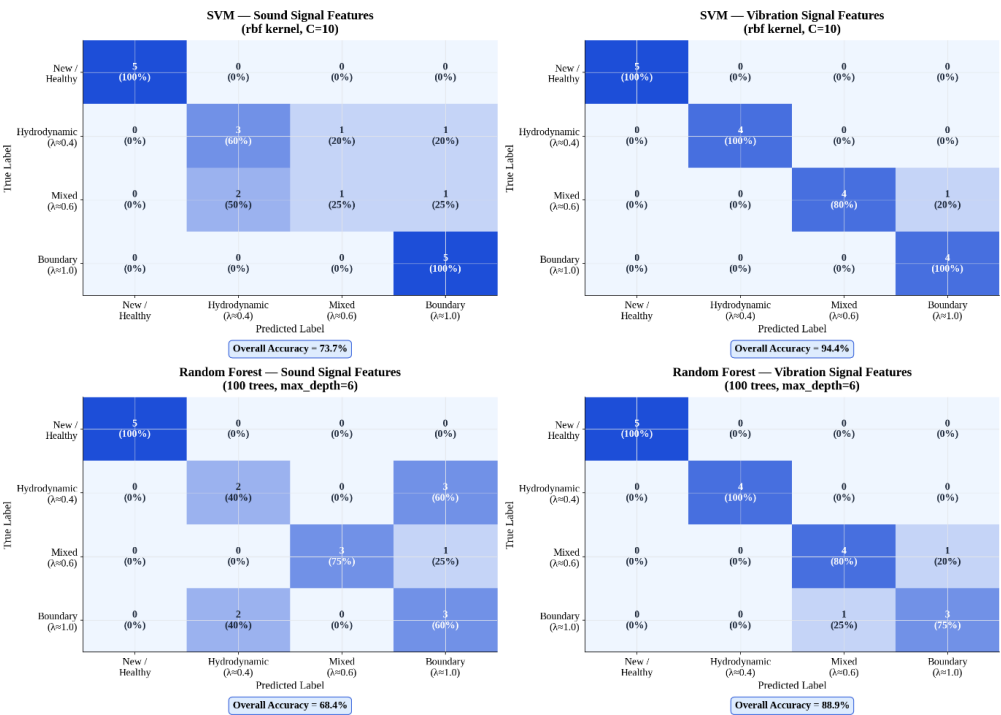


Fig.3. Confusion Matrix

Conclusion

The major findings of the present work can be summarized as follows:

- Differences in lubrication regimes in SKF NJ 307 ECP bearing generate identifiable and quantifiable changes in the nature of vibro-acoustic signals, and the film thickness (λ) used to correlate lubrication conditions is a convenient parameter.
- LMD is able to break down complex and non-stationary signals into physically meaningful Product Functions (PFs). Lubrication conditions are very sensitive to the energy distribution across the PFs with the boundary lubrication concentrated energy in high-frequency PF1 and the hydrodynamic lubrication distributing energy across lower-frequency PFs.
- Acoustic signals are more sensitive to change of lubrication regime than vibration signals, are more varied in kurtosis and crest factor, and feature separability better. This points out the benefit of microphone-based sensing of lubrication.
- However, vibration-based features provide superior class separability and classification performance in the proposed framework. This indicates that while acoustic signals effectively capture localized contact phenomena, vibration signals offer more robust feature representations for machine learning-based lubrication regime classification.
- The SVM classifier trained on LMD-derived features achieved the highest classification accuracy of 94.4% using vibration signals, significantly outperforming acoustic-based models (73.7%).
- The suggested methodology offers a non-invasive and real-time potent solution to proactive lubrication monitoring, allowing to detect the degradation of lubricants in advance before the local defects occur, thus being superior to the conventional fault-based diagnostic techniques.

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