Advanced Detection of REB Defects through Sound Emission using Envelope Analysis and Spectral Kurtosis

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Abstract: - Rolling elements bearings (REBs) are considered between the critical components in rotating machinery and their failures can provoke severe damage to the machine. Monitoring the condition of these components is essential to ensure the availability of the machine and improve its reliability. This article presents a low-cost acoustic approach based on the smartphone to monitor the bearing components. This approach stands on the use of a stethoscope connected to the smartphone via input Jack, to acquire the acoustic emission of the bearing at specific points. Firstly, the Hilbert transform (HT) was performed on acoustic signals to derive the envelope signal. Then, the Fast Fourier Transform (FFT) was applied to calculate the spectrum of the envelope signal. In the case of a noisy envelope spectrum where the fault signature is not noticeable, the Spectral kurtosis (SK) will be implemented to design an optimal filter to filter the acoustic signal using the Fast Kurtogram. After the filtering step, the process will be repeated to calculate the envelope spectrum. This study evaluates a defective bearing with a small inner race fault under different operating speeds (648, 1240, and 1816 rpm). Finally, the experimental results indicate that the proposed approach shows good results compared to the theoretical results for the early detection and identification of bearing failures. Furthermore, this technique is highly cost-effective and practical for rolling bearing condition monitoring.

Key-Words: - Bearings failures, Sound Emission, Envelope Analysis, Spectral kurtosis, Kurtogram.

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1. Introduction

Rolling bearings are one of the essential components in machines, and their failure is one of the most frequent causes of machine breakdown. Their defects generate an undesirable vibration and an unwanted acoustic noise. These components need to monitor their health to avoid the dangerous consequences of the machine.

Among the techniques of condition monitoring, vibration monitoring is currently the most used to monitor the degradation of these components and to ensure the reliability of the installation using specific statistical indicators such as RMS, kurtosis, crest factor, etc. The evolution of computer technology and signal processing techniques have made it possible to set up a robust monitoring system. Sometimes these indicators are not sensitive to changes in vibration [1], especially in the event of emerging and aggravated faults, which need advanced techniques to filter the vibration data and increase the fault signature in the signal. Also, acoustic emission (AE) analysis is a generally applied approach for monitoring the condition of bearings [2, 3] and identifying the deformation and failure processes [4]. An essential part of this work is to propose an acoustic approach to diagnose and identify bearing failures using inexpensive equipment based on the smartphone. This approach based on the acoustic emission signals with the sampling rate of 44.1 kHz and exploits the envelope analysis technique to extract rolling faults from this acoustic data, using the Hilbert Transform (HT) as the envelope extractor of the acoustic signal [5]. The difficulty in working at the audible range of acoustic emission is the background noise and sound emitted by the closest machines. To reduce this interference, we proposed to use a stethoscope to collect acoustic data at specific points on the bearings, as shown in Fig.4.

Acoustic emission (AE) in the field of structural health monitoring is defined as the generation of elastic waves resulting from a rapid and sudden redistribution of particles within or on the surface of a material. In recent years, predictive maintenance of rotating machinery has made significant progress in the oil and gas and marine industries. These advances have led to a very reliable technique based mainly on combining the vibration signals and AE signals in monitoring [6]. In the field of bearing diagnosis, A. Amini, M. Entezami and M. Papaelias [7], applied the envelope analysis as a useful tool to detect and evaluate damage in the bearings, based on acoustic emission measurement carried out on railway wheel sets. Their results indicate that the envelope analysis of the acoustic emission signal can detect and evaluate defective axle bearings and their characteristic defect frequencies under real world conditions. Similarly, the study [8] exploits the statistical parameters and frequency analysis of acoustic signals to detect the bearing failures. The results show that statistical parameters can be useful in identifying the types of defects in rolling bearings. This study mainly used the scalar indicator in the evaluation of the bearing failures.

Advanced studies were carried out to identify the bearing faults, using an advanced method of filtering the vibration data and enhance the ratio signal to noise (SNR). N. Sawalhi and Robert B. Randall [9], present the application of spectral kurtosis as a useful tool to enhance the bearing defect signature. Also, [10] verified the potential of spectral kurtosis (SK) to improve the signature of a localized bearing fault in induction machines using real vibration data sets collected in the laboratory. The SK was applied to identify the resonance frequency where the maximum changes for determining the envelope analysis parameters, including the filter bandwidth and the center frequency by a Short Time Fourier Transform (STFT). These studies present the SK as a powerful tool for designing an optimal filter able to isolate the fault signature based on the Kurtosis concept.

In this paper, the approach is mainly based on acoustic data recorded by the smartphone via a portable stethoscope, as shown in Fig.4. A contrast test was performed to evaluate and justify the use of the stethoscope based on the Kurtosis indicator, see Fig.7 and Fig.8. This test evaluates a healthy and faulty rolling bearing at different speeds with and without the stethoscope. The main idea of this study is to carry out an acoustic measurement using a manipulated stethoscope connected to the smartphone on a test bench [11] built by us to evaluate the ability to extract bearing defect frequencies as acoustic signals. In methodology, we first used the Hilbert transform (HT) to derive the envelope signal. Then, the Fast Fourier Transform (FFT) was used to compute the spectrum of the envelope signal. In the case of a noisy envelope spectrum where the fault signature is not perceptible, spectral kurtosis (SK) will be used to design an optimal filter for filtering the acoustic signal using fast Kurtogram. After the filtering operation, the same process will be repeated to calculate the envelope spectrum. This study evaluates a faulty bearing with a small inner race defect, as shown in Fig.4, under different operating speeds (648, 1240, and 1816 rpm). Finally, the experimental results indicate that the proposed approach shows good results compared to the theoretical results for the early detection and identification of bearing failures. For the lowest speed (648 rpm), SK was applied to improve the fault signature, which enhances the envelope spectrum and subsequently improves fault identification, as shown in results. Besides, this technique is very cost effective and convenient for monitoring bearing condition.

2. Theoretical background

2.1. Bearing fault signature

Rolling bearings generate vibrations and noise even if they are in good condition. When the bearing is rotating, the position of the rolling elements (balls) changes according to the shaft rotation. The relative position of the balls produces vibrations due to the change in the total stiffness of the bearing assembly [12]. In addition to the vibrations that occur in the bearings due to the relationship between the load and the position of the balls. In the case of the occurrence of a localized defect such as pitting, spalling, and cracking on the outer ring, the inner ring or the rolling element causes an increase in overall vibration and sound levels. These defects generate a short pulse in the signal. This impulse, caused by a sudden force that excites the structural resonance zones of the bearing resulting in damped high-frequency oscillations.

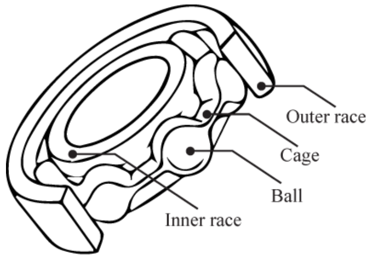


Fig 1. Components of a rolling bearing.

The theoretical values of frequencies of bearing defects are calculated from the geometrical dimensions of the bearing and the rotational frequency (Fr) of the shaft, [13] as shown below:

- Ball Pass Frequency Outer Race, in Hertz

$$BPFO = \frac{N}{2} \times F_r \times (1 - \frac{B}{P} \times \cos(\theta)) \quad (1)$$

- Ball Pass Frequency Inner Race, in Hertz

$$BPFI = \frac{N}{2} \times F_r \times (1 + \frac{B}{P} \times \cos(\theta)) \quad (2)$$

- Ball Spin Frequency, in Hertz

$$BSF = \frac{P}{2B} \times F_r \times \left[1 - \left(\frac{B}{P} \times \cos(\theta)\right)^2\right] \quad (3)$$

- Fundamental train frequency (Cage), in Hertz

$$FTF = \frac{F_r}{2} \times (1 - \frac{B}{P} \times \cos(\theta)) \quad (4)$$

Where,

- N = Number of balls
- F_r = Shaft rotational frequency (Hz)
- B = Ball diameter (mm)
- P = Pitch diameter (mm)
- θ = Contact angle. (θ = 0 degree in our case)

The frequencies of bearing failures are not evident in the frequency spectrum [13]. The spectrum of the defective bearing generally shows the energy concentration and large peaks in the high frequency range when the impacts excite various structural resonances of the bearing. When such characteristic frequencies appear (have a significant amplitude) in the spectrum of the analyzed signal, it is possible to identify a bearing defect and its location. However, it is complicated to extract these components because they have low amplitude and are merged with other spectral components and background noise.

It is also important to note that the signals produced by bearing faults (localized or extended) are generally non-stationary, i.e., signals whose statistical parameters vary over time. Specifically, localized bearing defect signals can be modeled as cyclostationary signals [1, 13]. It is also possible for a small localized defect to become an extended defect as the defect evolves over time. Regardless of the type of fault, in general, bearing failure can be detected using envelope analysis.

2.2. Fault detection

Bearing defects can be classified as either localized or extended. Where localized defects are usually associated with small pits or splinters. That produces sharp pulses that cover a wide bandwidth. On the other hand, the effect of extended faults is not noticeable or prominent in the spectrum, and its bandwidth is limited. Between the efficient techniques to extract to bearings faults, the envelope analysis where the HT and the FFT will be used as main tools to obtain the envelope spectrum of the original signal. Regardless of the type of fault, in general, bearing failure can be detected by envelope analysis [13]. In order to enhance the SNR of the signal, there is the SK used as a useful tool to design an optimal filter via the Kurtogram algorithm to increase the fault signature into the signal [13, 14].

2.3. Envelope analysis

Through the years, envelope analysis on high-frequency resonance demodulation has been widely used to identify localized defects in bearings. Each time a bearing component strikes the fault surface, a mechanical shock occurs. As a result, an impulse is generated, and the structural resonances of the system are excited by it. In addition, these pulses are amplitude modulated. In this way, through envelope analysis, it is possible to obtain demodulated signals, which are directly related to the rolling condition [1].

As mentioned above, the bearing defect signals can be considered as an amplitude-modulated signal, so that the carrier frequency, represented by high-frequency resonances, is modulated by the characteristic frequencies of the bearing resonance. The Hilbert transform can be used for the demodulation process in envelope analysis when the modulated signal proves to be analytical [5].

2.4. Spectral Kurtosis and the Kurtogram

When a bearing defect excites the resonance zones of the bearing in the rotating machine, modulations are produced at the natural frequencies of the bearing. Therefore, the characteristic frequency components must be demodulated using an optimal selection of center frequency (Fc) and bandwidth (Bw) for the identification of bearing defects based on envelope analysis. In this sense, spectral kurtosis based algorithms, such as Kurtogram, aims to find this combination in a computationally efficient way [14, 15].

Initially, spectral kurtosis (SK) was defined on the basis of the short-term Fourier transform (STFT) for the measurement of frequency-dependent impulsivity [9]. Thus, a spectral kurtosis of a signal means the calculation of the kurtosis value for each frequency; the SK can be calculated as follows:

$$SK(f) = \frac{\langle X^4(t,f) \rangle}{\langle X^2(t,f) \rangle^2} - 2 \tag{5}$$

The kurtosis for each frequency can be computed by taking the fourth power of $X(t,f)$ at each time and averaging its value, then normalizing it by the square of the mean square value. It has shown that if 2 is subtracted from this quotient, as shown in Eq.5, the result will be zero for a Gaussian signal. It should be noted that the results obtained from SK depend on the parameters chosen for the STFT, such as the length of the window, which may directly affect the calculation. Therefore, when considering an impulsive signal, a window shorter than the spacing between two consecutive pulses and longer than an individual pulse should provide a maximum kurtosis value [1].

For envelope analysis, in order to obtain an optimal result, it is of the utmost importance to correctly specify the center frequency and the bandwidth of the filter. For this reason, the Kurtogram concept emerges as a tool for finding the optimal filter for envelope analysis based on kurtosis spectral values [16]. Kurtogram presents the SK values as a function of the frequency and length of the windows, which define the spectral resolution.

Unfortunately, the Kurtogram was costly in time and inefficient to analyze all possible combinations of window frequency and length. The fast Kurtogram algorithm presented by J. Antoni [17], was developed as an extension of the Kurtogram, which calculates the spectral kurtosis using digital filters, instead of the STFT, following a so-called 1/3 binary decomposition tree.

3. Methodology

Generally, when an impact occurs in a faulty rolling element, an impulse occurs, which causes the excitation of the natural frequencies of bearing structure. The purpose of the envelope analysis technique is to eliminate the disturbance influence and to highlight the fault signature using the envelope spectrum. In practical applications, the natural frequencies of the bearing structure may change as a result of the different types of bearings. In the early stages of bearing defect evolution, it is less likely to be detected using conventional power spectral analysis (FFT). Where envelope analysis provides an efficient method of extraction from a low signal-to-noise ratio (SNR) from vibration or acoustic emission signals.

Fig.2 shows the diagram of the proposed acoustic approach followed in this work to detect and identify the bearing faults based on acoustic data.

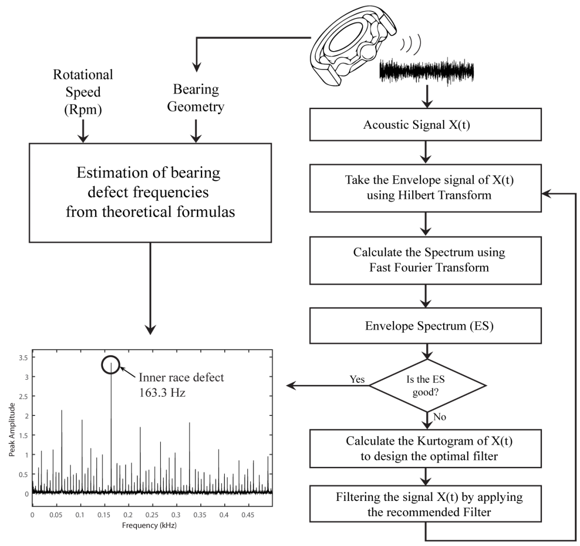


Fig 2. Diagram of proposed acoustic approach.

In this case, the methodology followed in this work consists of acquiring the acoustic signal $X(t)$ using a stethoscope connected to the smartphone. Then, extract the envelope signal of $X(t)$ using HT. Follow-up computation of the envelope spectrum using the FFT algorithm. In the case of a noisy envelope spectrum, the user may decide to filter the acoustic data by applying the Fast Kurtogram to design an optimal filter based on spectral kurtosis. In the end, the theoretical frequencies of the bearing faults were estimated from Equations 1, 2, 3, and 4 presented above to help the user identify the faults. These theoretical values are based on shaft rotation frequency and bearing geometry.

It is also significant to remark that since defects are identified in the spectrum of the envelope, its magnitude can be used as an index of severity. In this way, the evolution of a defect can be analyzed as a function of the increase of the natural frequency amplitude of the bearing.

4. Experimental setup

In this section, healthy and damaged bearings (Model 6004, grooved ball bearing, Table I) are installed on a rotor system, illustrated in Fig.4, supplied by Gunt Company [11]. The defective bearing has been artificially damaged in the inner ring, as shown in Fig.3, this small defect simulates a localized defect in a bearing. Experiments were carried out to evaluate the detection and identification of bearing failures using acoustic emission analysis.

4.1. Laboratory bearing test rig

Laboratory tests were carried out on both healthy and defective bearings using a custom test rig under three different rotating speed, 648, 1240, and 1816 revolutions per minute (Rpm).

Table I present the geometrical characteristics of the rolling elements bearing used in this works. (Model 6004, grooved ball bearing)

TABLE I. CHARACTERISTICS OF HEALTHY AND FAULTY BEARING

Bearing	Characteristics	Units
Type	6004, d = 20, D = 42, B =12	-
Pitch diameter (P)	31	mm
Ball diameter (B)	6.35	mm
Number of balls (N)	9	-
Contact angle (θ)	0	degrees

Fig.3 shows a picture of the defective bearing used in this study, with a small localized fault on the inner ring.

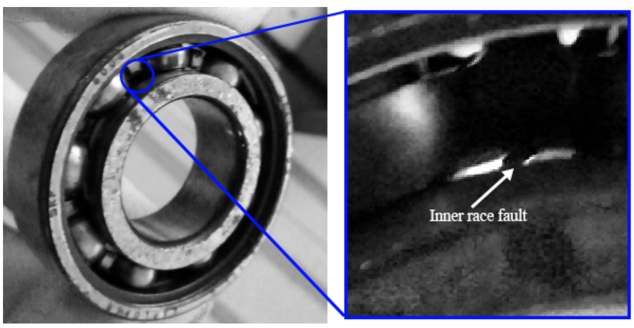


Fig 3. Damaged bearing used in the experimental tests (Inner race fault).

Fig.4 shows a photograph of the test rig where the experiments on healthy and defective bearings were carried out.

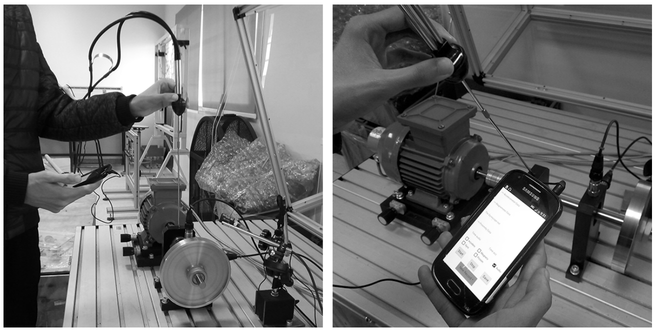


Fig 4. Photograph of the test rig for performing the experimental tests.

4.2. AE measurement

Acoustic signals from the bearings under different conditions were recorded using a mobile application called "VibroTeak" developed by our team. This application allows recording the acoustic signal in (.wav) format at a sampling frequency of $44.1\ kHz$. In addition, the acoustic data were imported into Matlab using the "audioread" function for processing. Envelope analysis techniques and SK-based filtering were then applied using a Matlab program. Fig.5 shows the schematic of acoustic signal acquisition using a stethoscope connected to the smartphone via Jack Input.

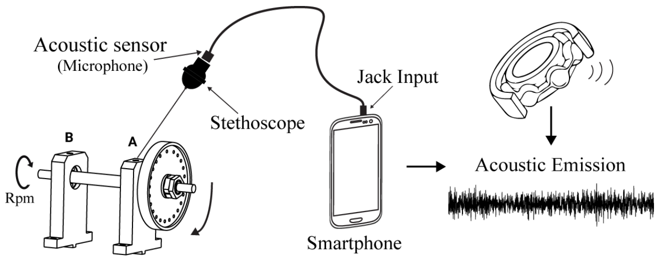


Fig 5. Schematic of acoustic signal acquisition using the stethoscope connected to the smartphone.

Acoustic signals from the bearings under different conditions were measured at three different speeds, 648, 1240, and 1816 rpm. Each experiment was conducted for healthy and defective bearings, which were used to identify the bearing failure and discuss this in detail the results of this proposed approach.

4.3. Contrast test of the stethoscope

This contrast test assesses the use of the stethoscope in this study. For instance, as we see in Fig.6, the time domain of the acoustic signal of the damaged bearing (inner race fault) with and without the stethoscope. Consequently, Fig. 6.a shows that the signal is more impulsive compared to Fig. 6.b at constant rotor speed (648 rpm). That is, the bearing defect signature appears more clearly in the stethoscope's acoustic data.

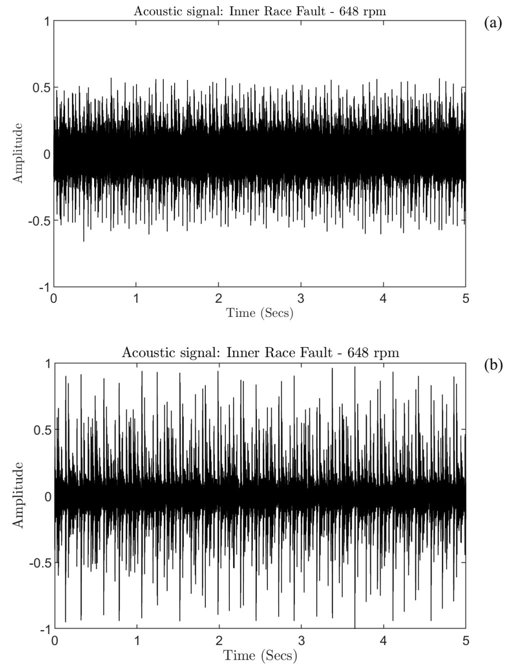


Fig 6. Acoustic signal of the damaged bearing in 648 rpm, (a). without a stethoscope, (b). with stethoscope.

To guarantee and generalize the results of the contrast test, this test will be extended to assess a healthy and defective bearing with a defect in the race ring at different speeds (648, 1240 and 1816 rpm). To assess the impulsivity of the acoustic signal, statistical kurtosis was applied to assess the impulsivity level as shown in Fig.7 and Fig.8.

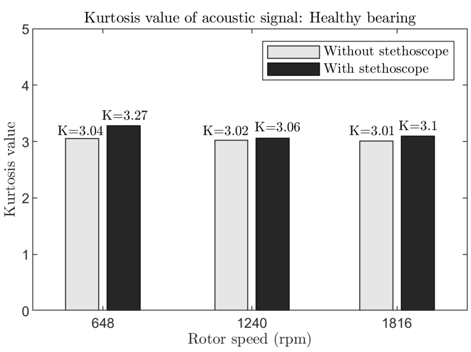


Fig 7. Kurtosis values of the acoustic signal of the healthy bearing, with and without stethoscope at different speeds.

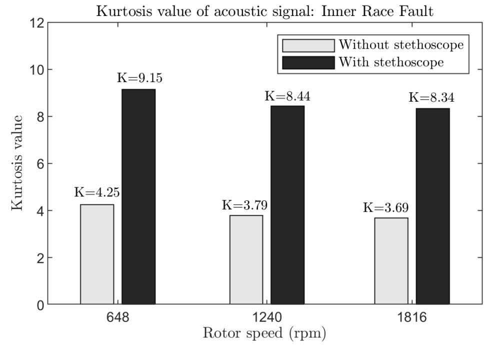


Fig 8. Kurtosis values of the acoustic signal of the damaged bearing, with and without stethoscope at different speeds.

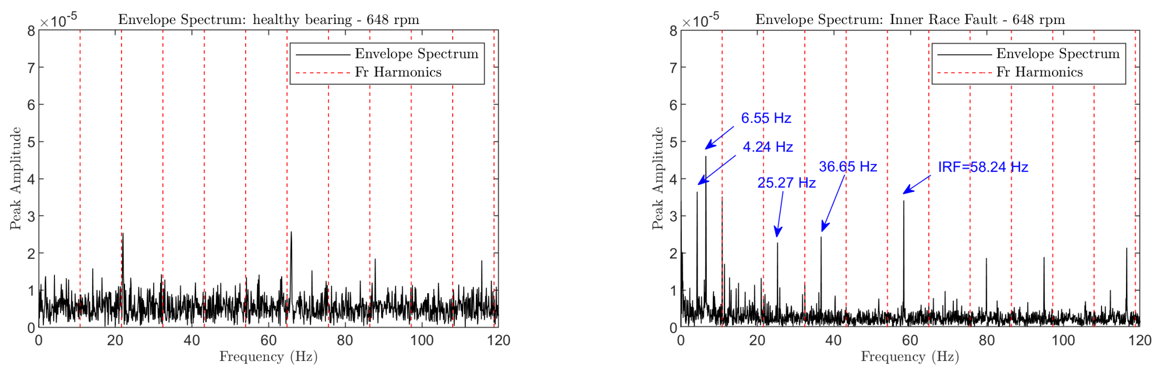
Under the same experimental condition, Fig.7 clearly indicates that with or without the use of the stethoscope, the kurtosis results are almost the same under all three operating speeds for a healthy bearing. Whereas, for the damaged bearing, there is a huge difference between the kurtosis value with and without the use of the stethoscope, as shown in Fig.8. This means the improvement of the fault signature in the acoustic signal, which assures the use of the stethoscope in this work and shows the important role that it plays in capturing the acoustic data at specific points.

5. Results and discussion

Table II shows the theoretical frequencies of bearing faults. These theoretical values are calculated using Equ.1, 2, 3, 4 based on the shaft rotational frequency (Fr) of the three speeds and the geometrical parameters of the bearing presented in detail in Table I.

TABLE II. THEORETICAL FREQUENCIES OF BEARING DEFECTS

Defect types	Speed (RPM)		
	648	**1240**	**1816**
FTF	4.28	8.21	12.01
BSF	25.23	48.33	70.69
BPFO	38.60	73.96	108.17
BPFI	58.50	112.07	163.9



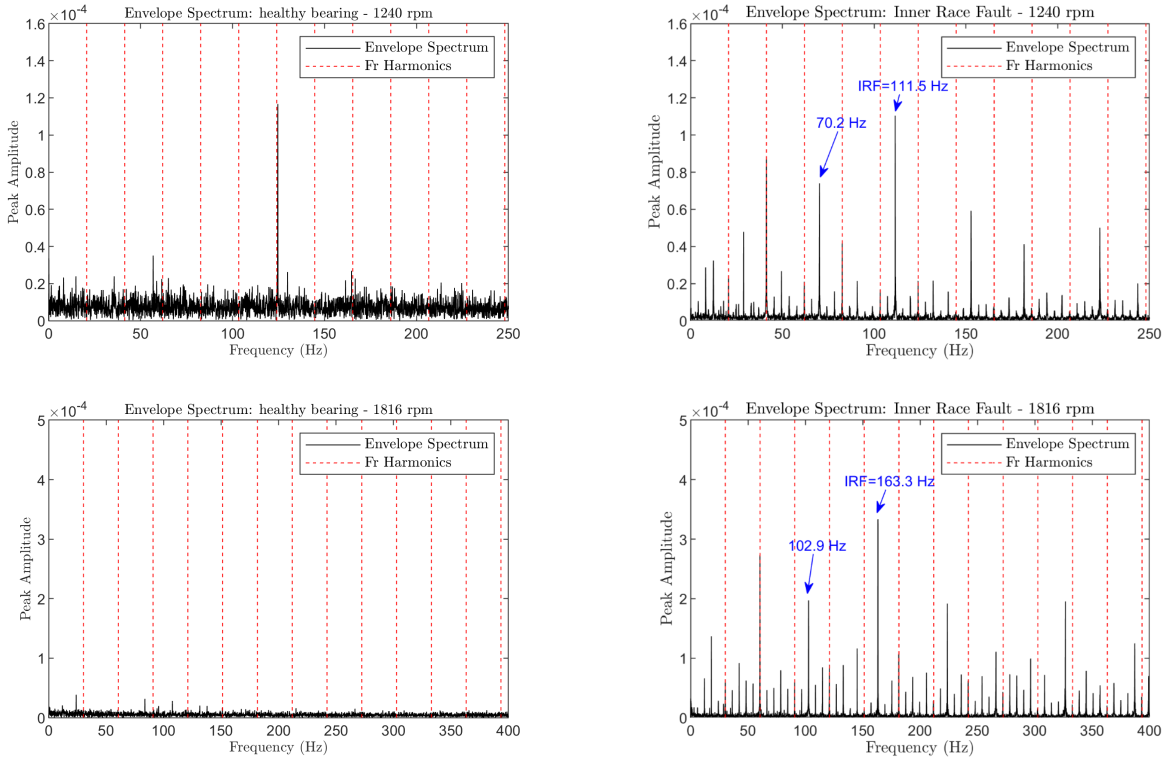


Fig 9. Envelope spectrum of the acoustic signal for a healthy and damaged bearing (internal stroke defect) at different rotor speeds (648, 1240, and 1816 rpm).

In this study, we implemented three experimental tests for each healthy bearing and defective bearing where a defect is located on the inner ring. Fig.9 illustrates, respectively, the envelope spectrum of the acoustic signal for each operating speed. The harmonics of the rotation frequency (Fr) have been indicated in the graphs for facilitating the reading by the user.

As mentioned earlier, bearings produce noise and acoustic emissions even if they are in good condition, as shown in healthy bearings graphs in Fig.9. In the case of the speeds 1240, 1816 rpm, the inner race fault (IRF) signature was evident and dominant in the envelope spectrum, 111.5 Hz, and 163.3 Hz, respectively. For healthy bearing, the figure shows that there is no indication in the envelope spectrum confirming the existence of a bearing fault for the three operating speeds versus the theoretical frequencies of faults (see Table II). Another remark, when the rotor speed was increased, the noise decreased, as indicated for the defective bearing, i.e., the defect signature becomes more significant in the acoustic signal. In addition, the characteristic frequency of the fault amplitude increases with the severity of the failure (according to rotation speed), which could be used as an indicator of the prognosis.

The inner race fault of the damaged bearing excites other bearing components, which has led to the occurrence of parasite frequencies related to the bearing components, in particular, the outer race frequency for the three speeds, respectively, 36.65 Hz, 70.2 Hz, 112.9 Hz as indicated in the figure.

For the same fault, the envelope spectrum of the speed 648 rpm is noisier compared to the other speeds. It shows that the fault signature is not the dominant peak, which means that the noise overlaps the fault signature and decreases the significance of the fault in the acoustic signal, i.e., the signal-to-noise ratio is further decreased. It should improve the acoustic signal to better show the fault signature and increase the SNR. For this purpose, an optimal filter will be designed to perform this SK-based mission via the fast Kurtogram; the next part will concern the improvement of the acoustic data obtained at this lower speed (648 rpm).

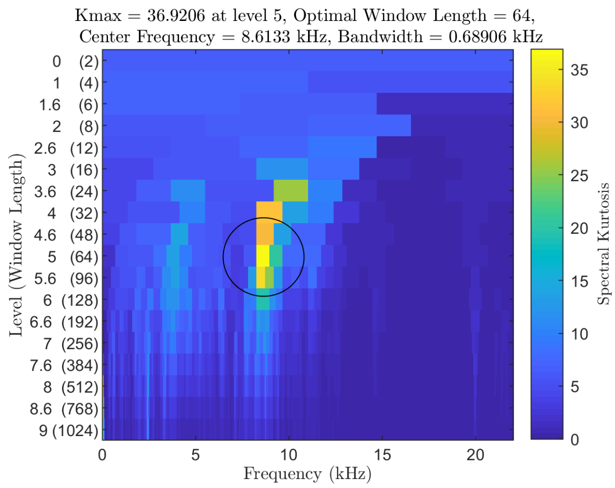


Fig 10. Fast Kurtogram color map of the damaged bearing at 648 rpm.

Fig.10 shows the Fast Kurtogram color map of the acoustic data (at 648 rpm). The black circle in the figure indicates the area where the Kurtosis value is higher ($K_{max} = 36.92$). The map suggests that the filter parameters are optimal. Where the center frequency $Fc = 8.6133\,kHz$ and the bandwidth $Bw = 0.689\,kHz$, at level ($k = 5$), and the optimal window $Wn = 64$. It should be mentioned that the optimum bandwidth frequency that was used in the envelope analysis was estimated as a function of the spectral kurtosis, as shown in Fig.11.

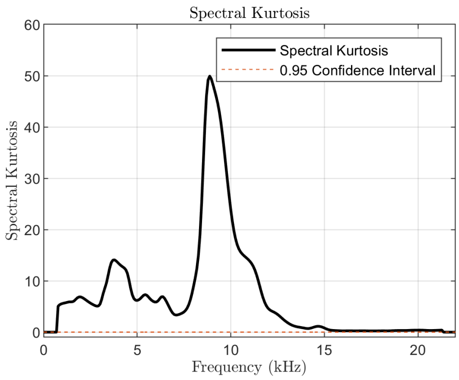


Fig 11. Kurtosis spectral with the optimal window (Wn=64) of the damaged bearing at 648 rpm.

After applying the optimal filter to the acoustic data, the same process will be repeated to recalculate the envelope spectrum of the damaged bearing signal. As a result, the envelope spectrum clearly shows the dominance of the IRF defect signature peak, with the amplitude around 6×10^{-5} as shown in Fig.12.

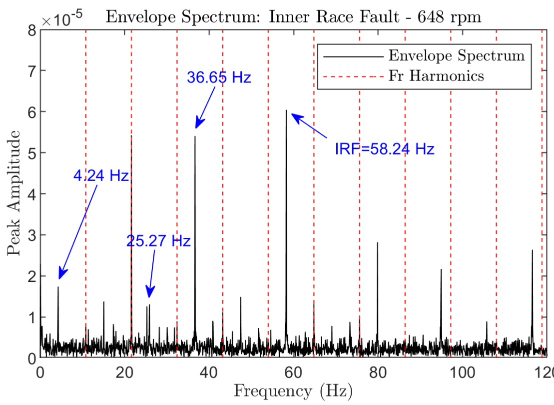


Fig 12. Envelope spectrum using SK of the damaged bearing in 648 rpm.

The results obtained confirm the proposed approach in this work, and therefore the theoretical concepts behind it. The frequency of inner race defect was detected for each damaged bearing experiment at the three different speeds, which strongly identified the bearing failure. In addition, the amplitude of the characteristic frequency of the defect increases with the severity of the defect (as a function of speed), which could be used as a prognostic indicator. Furthermore, in the envelope spectrum, it was also noticed that as the amplitude of the IRF increased, the amplitude of the other components decreased. With regard to the excitation of other bearing components due to the defect located in the inner race of the damaged bearing. Particularly, outer race frequency, as shown in Fig.9. In the case of the operating speed 648 rpm, this frequency (36.65 Hz) remains with a higher amplitude even after the filtering process, as shown in Fig.12.

In sum, it can be concluded that, although the analysis of the acoustic analysis is more complicated than vibration analysis, this acoustic approach based on the use of the stethoscope connected to the smartphone presents good results in failure detection of bearing.

6. Conclusion

This study describes an acoustic data-based approach for the detection and identification of bearing faults in rotating machines by applying spectral kurtosis and envelope analysis. This approach based mainly on the use of a stethoscope connected to a smartphone to acquire the acoustic data at specific points, thus reducing the cost of diagnostic equipment and decreasing the acoustic emissions from surrounded machines. The experimental tests performed using a test rig, where two bearings were evaluated, one healthy and the other with an inner ring defect at different operating speeds. The experimental tests show that the methodology presents good results compared to the theoretical estimate of bearing defects. Besides, the amplitude of the fault frequency can be used as an indicator of the severity of the fault. For industrial applications, this approach could be easily carried by professional and non-professional predictive maintenance teams, primarily due to its low-cost, high availability, and application advantages.

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References:

[1] Randall, R. B. (2011). Vibration-based condition monitoring: industrial, aerospace and automotive applications. John Wiley & Sons.

[2] Caesarendra W, Kosasih B, Kiet A, Zhu H, Moodie CAS, Zhu Q. Acoustic emission-based condition monitoring methods: review and application for low speed slew bearing. Mech Syst Signal Process 2016;72–73:134–59. doi: http://dx.doi.org/10.1016/j.ymssp.2015.10.020.

[3] Hase A, Mishina H, Wada M. Fundamental study on early detection of seizure in journal bearing by using acoustic emission technique. Wear 2016;346–347:132–9. doi: http://dx.doi.org/10.1016/j.wear.2015.11.012.

[4] Siracusano G, Lamonaca F, Tomasello R, et al. A framework for the damage evaluation of acoustic emission signals through Hilbert – Huang transform. Mech Syst Signal Process 2016;75:109–22. doi: http://dx.doi.org/10.1016/j. ymssp.2015.12.004.

[5] Luo, H., Fang, X., & Ertas, B. (2009). Hilbert transform and its engineering applications. AIAA Journal, 47(4), 923-932.

[6] Papaelias, M., Papailias, F., Kerkyras, J., & Kerkyras, S. C. (2009, September). Condition monitoring of oil and gas pumps and their driving equipment based on acoustic emission techniques. In non-destructive testing conference, Blackpool.

[7] Amini, A., Entezami, M., & Papaelias, M. (2016). Onboard detection of railway axle bearing defects using envelope analysis of high frequency acoustic emission signals. Case Studies in Nondestructive Testing and Evaluation, 6, 8-16.

[8] Kumar, S., Goyal, D., & Dhami, S. S. (2018). Statistical and frequency analysis of acoustic signals for condition monitoring of ball bearing. Materials Today: Proceedings, 5(2), 5186-5194.

[9] Sawalhi, N., & Randall, R. B. (2004, November). The application of spectral kurtosis to bearing diagnostics. In Proceedings of ACOUSTICS (pp. 3-5).

[10] Saidi, L., Ali, J. B., Benbouzid, M., & Bechhoefer, E. (2016). The use of SESK as a trend parameter for localized bearing fault diagnosis in induction machines. ISA transactions, 63, 436-447.

[11] PT500.12, GUNT Hamburg, Instruction pour expérience, Jeu d'accessoires: dommages sur les paliers à roulement, (2010) .

[12] Liu, J., & Shao, Y. (2015). A new dynamic model for vibration analysis of a ball bearing due to a localized surface defect considering edge topographies. Nonlinear Dynamics, 79(2), 1329-1351.

[13] Randall, R. B., & Antoni, J. (2011). Rolling element bearing diagnostics—A tutorial. Mechanical systems and signal processing, 25(2), 485-520.

[14] Antoni, J., & Randall, R. B. (2006). The spectral kurtosis: application to the vibratory surveillance and diagnostics of rotating machines. Mechanical systems and signal processing, 20(2), 308-331.

[15] Antoni, J. (2006). The spectral kurtosis: a useful tool for characterising non-stationary signals. Mechanical systems and signal processing, 20(2), 282-307.

[16] Ho, D., & Randall, R. B. (2000). Optimisation of bearing diagnostic techniques using simulated and actual bearing fault signals. Mechanical systems and signal processing, 14(5), 763-788.

[17] Antoni, J. (2007). Fast computation of the kurtogram for the detection of transient faults. Mechanical Systems and Signal Processing, 21(1), 108-124.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The author contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

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