Contribution to the improvement of the sensitivity of the scalar indicators

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Abstract :

The aim of this article is to show the interest the wavelet transforms in improving the sensitivity of the scalar indicators (kurtosis and crest factor) in the context of conditional maintenance by vibratory analysis of rotating machinery. When the bearing is damaged, the appearance of a crack on the gear tooth disturbs signal. This change is due to the presence of periodic pulses. Nevertheless, the presence of noise induced by the random excitation can have an inuence on the values of these time indicators. Denoising of these signals by wavelet transform allows improve the sensitivity of these indicators and to increase the reliability of diagnosis. To simulate the signal to be analyzed, we voluntarily introduced a default. We selected wavelet Daubchies type that is well suited to this type of problem. The purpose is to try to master the various parameters related to the wavelet analysis for reliable and inexpensive detection, namely, the order of the wavelet and the level of decomposition. The approach is to observe the kurtosis and the crest factor for several wavelet orders depending on the gravity of the fault.

Keywords: Condition monitoring, Rolling element bearings, De-noising, Wavelet transform, Kurtosis

1 Introduction

In the field of prognostics and health monitoring, different methods are commonly employed for faulty bearing detection. A faulty bearing will typically create periodic, impulsive vibrations, which are proportional to rotational speed. These vibrations may be recorded and analyzed to reveal the nature of a given fault. Rolling element bearing is a major source of failure in electromechanical systems. Recently, the use of diagnostics and prognostics methodologies assisted by artificial intelligence tools such as artificial neural networks, support vector ma-chines etc. have increased for assessing the health of the rolling element bearings. The effectiveness of these approaches largely depends upon the quality of features extracted from the bearing signals. Keeping this in mind, the authors have presented the various signal processing methods applied to the fault diagnosis of rolling element bearings with the objective of giving an opportunity to the examiners to decide and select the best possible signal

analysis method as well as the excellent defect representative features for future application in the prognostic approaches. In their bibliographical review Rai [1], first quotes some of the condition monitoring tools used for rolling element bearings and then the importance of signal processing methods in diagnosis and prognosis of rolling element bearings. Next, it discusses the various signal processing methods and their diagnostic capabilities by dividing them into three stages: first stage corresponding to the articles published before the year 2001, second stage refers to the articles published during the period 2001-2010 and lastly the third stage pertains to the articles issued during the year 2011 to till date. To focus more on the recent developments in the signal processing methods, the third stage has been partitioned further into several sections depending upon the methodology of signal processing.
Their relative advantages and disadvantages have been discussed with regard to the fault diagnosis of rolling element bearings. The wavelet transform outper-forms the Short-Time Fourier Transform (STFT) in terms of temporal resolution, which allows a greater exibility in the analysis of non-stationary signals. Rioul [2] has been also demonstrated that wavelet denoising requires no knowledge of the noise level in order to optimally elimi-nate Donoho [3]. Much researches have been conducted to focus on the envelope analysis from the signal located in certain specific frequency bandwidth. Jimnez [4] used Hilbert and Wavelet transforms to make the fault diagnosis easier. In 2008, Chiementin [5] suggests a new form of wavelet, which is adapted to shock response, and a methodology for its use in which the parameters are determined automatically. Djebala [6], [7] presents a de-noising method of the measured signals is presented. Based on the optimization of wavelet multi-resolution analysis, it uses the kurtosis as an optimization and evaluation criterion, several parameters were then selected. The experimental results show the validity of this method within the detection of several defects simulated on ball bearings.
In 2009, Wang [8] proposes an improved combi-nation of the Hilbert and wavelet transforms to identify early bearing fault signatures. Real rail vehicle bearing and motor bearing data were used to validate the proposed method. A traditional combination of Hilbert and wavelet transforms was employed for comparison purpose.
An indicator to evaluate fault detection capabili-ty of methods was developed in this research. Tang [9] proposes an improved method that combines the energy operator demodulation and the dual reconstruction scheme in wavelet packet transform. A fan bearing test rig is established and the vibration signals collected from this test rig are used to validate the proposed method. The analysis results show that the proposed method has a good frequency resolution. Kulkarni [10], presents a methodology for fault diagnosis of rolling element bearings based on discrete wavelet transform (DWT) and wavelet packet transform (WPT). Further De-noising technique based on wavelet analysis was applied. The results show that wave-let packet node energy coefficients are sensitive to the faults in the bearing. The feasibility of the wavelet packet node energy coefficients for fault identification as an index representing the health condition of a bearing is established through this study.
The wavelet de-noising technique with wavelet based function has been used in the work of El-Tobi [11] for bearing fault detection. The applications of the wavelet de-noising show that the fault pulses in time-domain of the de-noised signals are easily to be detected as a result of removing the covering noise, which is not possible through the time-domain analysis of the original signal. Further more, the reciprocal period which matches the bearing fault frequency can be easily detected without further analysis by FFT-Spectrum.
The aim of this article is to show the interest of wavelet transform for the improvement of the sensitivity of scalar indicators (crest factor, kurtosis) within the application of conditional maintenance by vibratory analysis.

2 Numerically Simulated Signal

The main source of the vibration in the shaft bearing system is the presence of the defect on the interacting bearing components. Many research papers have been published in last few decades on the detection of the defects in rolling element bearings. The dynamic models of rolling element bearing with local and distributed defects have been reviewed in Shaha [12]. The numerically simulated signal that has been chosen is similar to the signal used in Sheen [13] with added noise. Its mathematic formulation is given as:

$$x(t)=\sum_{n} e^{-\beta \breve{t}}\left[A\sin\left[2\pi f_1(t-n\tau)\right]+B\sin\left[2\pi f_2(t-n\tau)\right]\right]+b(t) \tag{1}$$

$$\breve{t}=\mathrm{Mod}\left(t,\frac{1}{F_m}\right) \tag{2}$$

Where β the structural damping characteristic frequency, F_m is the bearing fault frequency (BPFO equal to 100 Hz), A = 1, and B = 1. f_1 and f_2 are the two resonant frequencies (equal to 2000 Hz and 3000 Hz, respectively). A normally distributed random signal with 0 mean and standard deviation of 0.07 is added into the simulated signal. The signal is shown in Fig. 1.

Time-frequency techniques show potential for detecting bearing problems in more complex rotating machines where the SNR is low and many frequency components are present, as in the common occurrence of multiple defects Bhende [14].

3 Optimization of multi-resolution wavelet analysis

For a long time FFT was the tool of choice to address this problem, except that it was always di_cult to avoid altering the signal by reducing a large amount of noise.

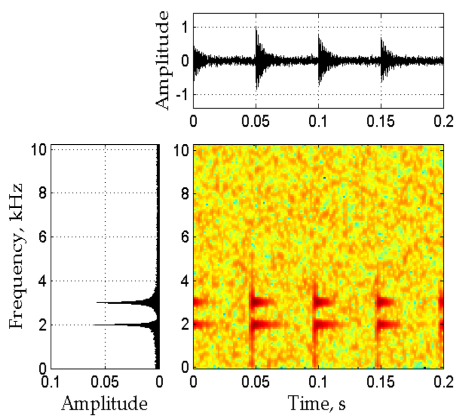

Figure 1. Spectrogram of the simulated signal

Methods based on thresholding wavelet transform have emerged to _ll the gaps Donoho [15], [16], Johnstone [17] and Chang [18]. Their strength resides in their ease of implementation and their effectiveness. Therefore the main idea is to remove the small coefficients responsible for the noise in the signal. The denoising of the noisy signal using wavelet transform is obtained in three basic steps Kumar [19]:

(1) Signal decomposition: Signal is decomposed into j level of wavelet transform and coefficients

are calculated.

(2) Thresholding: Then the threshold is selected and the detail parts through wavelet transform are compared with the threshold and the detail parts are set to zero if they are less than the threshold.

(3) Signal reconstruction : Finally the signal is reconstructed using the original approximation coefficients of level j and modified detail coefficients.

Soft and Hard thresholding In the literature there are two types of thresholding techniques applicable to signal processing which are Hard thresholding and Soft thresholding. Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards zero. The drawbacks of the Hard and Soft thresholding are that the Hard threshold is not continuous at threshold where as the Soft threshold is not differentiable at this value; a pre-requisite for any optimization problem Kulkarni [10]. If denotes _ the given threshold, the Soft threshold can be defined by Johnstone [17]:

$$T_{Soft}(x)=\begin{cases} sign(x)(|x|-\lambda) & |x|\geq\lambda \\ 0 & |x|<\lambda \end{cases} \tag{3}$$

and Hard thresholding can be written as:

$$T_{Hard}(x)=\begin{cases} x & |x|>\lambda \\ 0 & |x|\leq\lambda \end{cases} \tag{4}$$

With the above thresholding methods in place the obvious question is how to set an appropriate value of λ. A widely adopted approach, introduced by Donoho [15], is to use the universal threshold. For a series of length N the universal threshold is given by:

$$\lambda=\sigma\sqrt{2log(N)} \tag{5}$$

where λ is the threshold value, N is the length of the noisy signal. In threshold selection, we should not ignore the detail coefficients in every level that probably inuence the robustness of the threshold estimating. So we have to rescale a selected threshold in some level. In this paper, the threshold is dependent on the detail coefficients at every level. The standard deviation σ is thus estimated by:

$$\sigma=\frac{median(|d_1|)}{0.6745} \tag{6}$$

3.1 Methodology for performance evaluation

To evaluate the performance of our approach several assessment tests such as Signal to Noise Ratio (abbreviated SNR) is employed. SNR is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power, often expressed in decibels. The global SNR values are determined by the following equation:

$$SNR_{dB}=10log_{10}\left(\frac{\sum_n x^2(n)}{\sum_n[x(n)-\hat{x}(n)]^2}\right) \tag{7}$$

3.2 The choice of analyzing wavelet

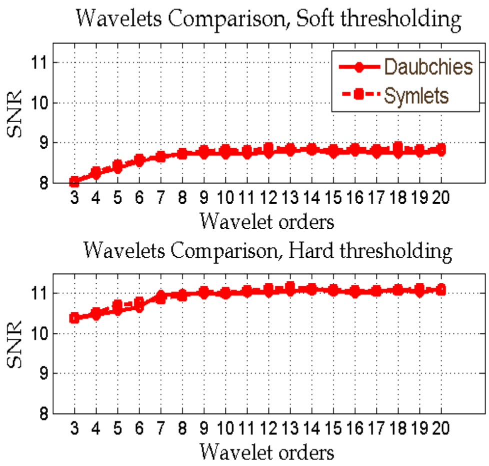

Figure 2. SNR vs different wavelet orders

The study of the choice of analyzing wavelet will be conducted on the basis of a test of several wavelets. This will be on the study of SNR between the original signal and the signal after reconstruction. The analyzing wavelet chosen will be the one who will present the value of the highest SNR. We apply Mallat algorithm multiresolution analysis using the analyzing wavelet for different orders. The most analysands wavelets used are Daubechies (db) and Symelet (sym). White Gaussian noise is added to the simulated signals. The noisy signal is represented in Fig.1, for SNR value. Firstly, this signal is denoised using wavelet transform with the methods of soft and hard thresholding. For comparison with the same conditions, the parameters of the wavelet transform are set for both cases. The wavelet decomposition family is the db9 and level 6 is selected.

In order to illustrate performance of the proposed threshold selection, the signal is corrupted by noise at different level of SNR. These noisy signals are denoised using wavelet transform with universal thresholds. SNR out is used as performance measure for denoising. Fig.2 shows that practically there is no appreciable difference between the two wavelet family and the Hard thresholding method clearly has the best performance for these white noise conditions. The output SNR of the Hard thresholding method shows the SNR improvement as compared with soft thresholding.

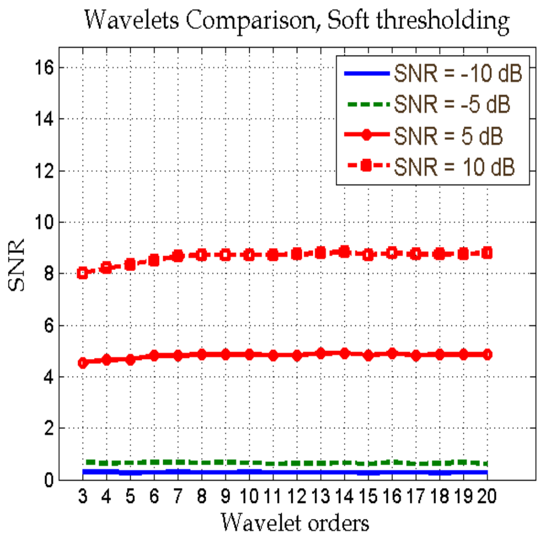

Figure 3. SNR vs different noisy signal (Soft thresholding)

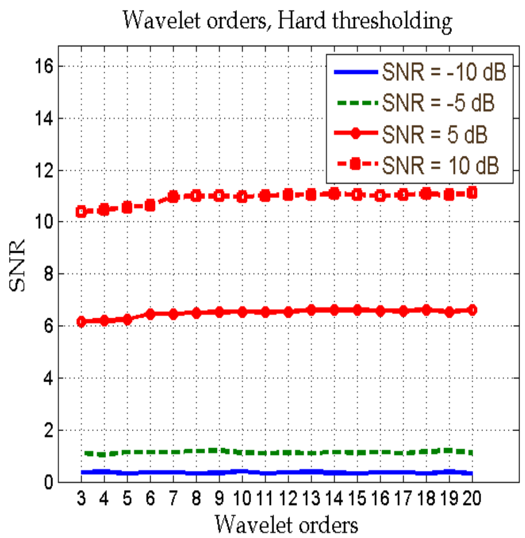

Figure 4. SNR vs different noisy Signal (hard thresholding)

3.3 Statistical Parameters

To obtain useful information from the time-domain acoustic and vibration signals various statistical techniques have been developed over the years. One of the parameters, namely, the crest factor, which is deffined as the ratio of maximum absolute value to the RMS value of the vibration signal, gives an idea about the occurrence of impulse in the time-domain signal. In real-time condition monitoring, an increased value of the crest factor over a period of time indicates the presence of wear or pitting. Another powerful parameter called kurtosis measures the degree of peakiness of a distribution compared to a normal distribution Jena [20].

Mathematically, crest factor and kurtosis for signal x(n) with N number of samples in the time domain can be expressed as the Root Mean Square (RMS) of the acceleration. It is defined by:

$$A_{RMS} = \sqrt{\frac{1}{N}\sum_{n}\left[x(n) - \bar{x}(n)\right]^2} \tag{8}$$

with $\bar{x}$ the mean of the time series x(n). Kurtosis is a statistical parameter allowing the analysis of the distribution of the vibratory magnitudes contained in a time domain signal. It corresponds to the moment of fourth order divided the square of the standard deviation:

$$Kurtosis = \frac{\frac{1}{N}\sum_{n}\left[x(n) - \bar{x}(n)\right]^4}{\left[\frac{1}{N}\sum_{n}\left[x(n) - \bar{x}(n)\right]^2\right]^2} \tag{9}$$

The Crest Factor is another time domain criterion consisting in the ratio between maximum magnitude of the time signal and A_{RMS} :

$$CrestFactor = \frac{max\left[x(n)\right]}{A_{RMS}} \tag{10}$$

4 Application to the Early Detection

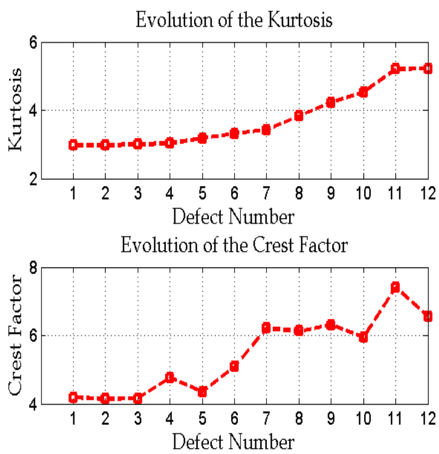

Figure 5. Kurtosis and Crest Factor evolution vs the degradation rate

It is clear from Figure 5 that in the case of original signals, statistical indicators have increased considerably, implying a degradation of bearing condition. The Kurtosis and the crest factor so operate always increasingly longer depending on the aggravation of the defect. From the default number 8, the

Kurtosis and the crest factor begins to be higher and their progression is substantially proportional to the amplitude of the default.

An improvement of the kurtosis and of the crest factor sensibility can be noticed. It can also be noticed that those two indicators (crest factor and kurtosis) do not vary in a linear manner when the size of the defect is very important Tandon [21]. Indeed, when the size of the defect is very important, the time space between two successive shocks becomes inferior to the relaxation time and the hypotheses on which the application validity lies on are not any more confirmed Pachaud [22].

The crest factor and the kurtosis value become inferior or equal to three and are not anymore characteristic of an impulsive signal Dron [23].

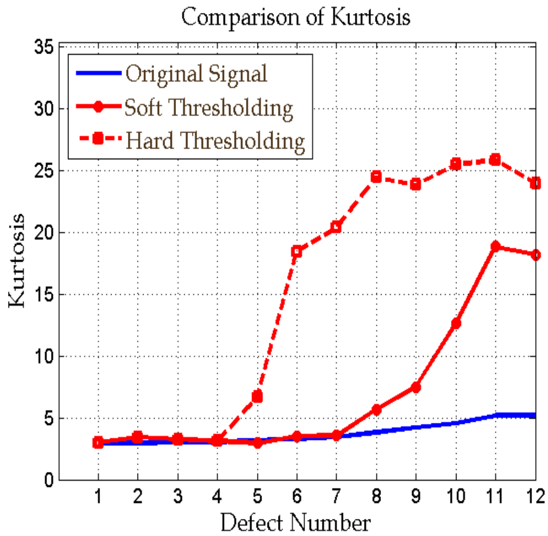

Figure 6. Comparison of original and reconstructed signals (Kurtosis)

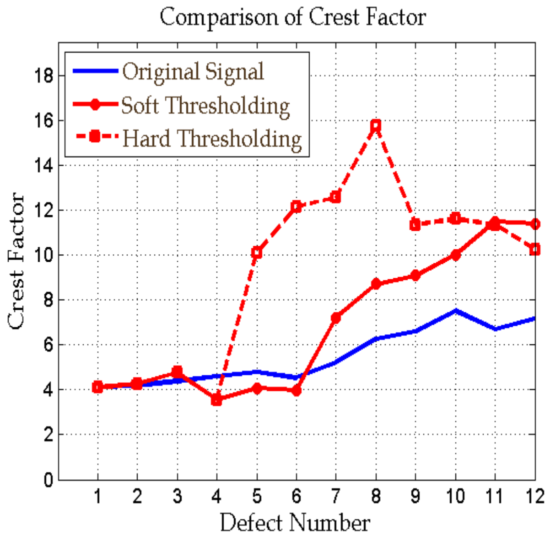

Figure 7. Comparison of original and reconstructed signals (Crest factor)

A comparison between the values of Kurtosis and Crest factor before and after the signal decomposition (Figure 6 and Figure 7 shows the contribution of wavelet transforms in improving the sensitivity of these indicators with respect to the conventional case Merzoug [24]. It is also noteworthy in this study that the soft thresholding is better adapted, as long as the results obtained are better.

5 Experimental application

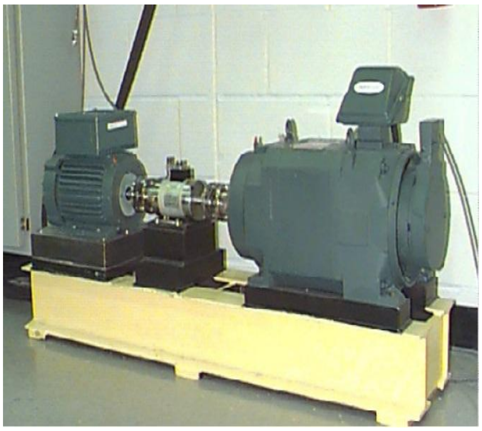

Figure 8. Published data setup from Loparo[26]

To verify the e_ectiveness of the proposed method, the experimental bearing fault data provided by Case Western Reserve University is analyzed here Loparo [26]. The data were collected from a test rig, as shown in Figure 8. The experimental setup mainly included a 2 hp motor (left), a torque transducer, and a dynamometer (right). The motor shaft was supported by 6205-2RS JEM SKF type bearings. The bearings inner race, outer race, and rolling elements were arti_cially seeded by a single point fault using electro-discharge machining, respectively. For the faults localized to the inner race, rolling elements, and outer race, the accelerometers were used to sample vibration signals at 12 kHz and were installed at the 12 o'clock, 3 o'clock, and 6 o'clock positions at the fan end, respectively. The data samples obtained from the different bearing health conditions are shown in Figure 9.

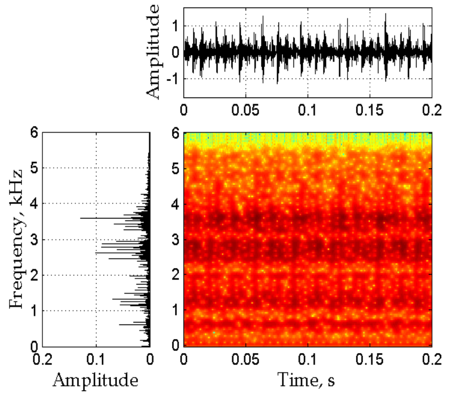

Figure 9. Spectrogram of the experimental signal

Two datasets of signals including health and three di_erent fault conditions are employed here for analysis. For each dataset, in the _rst layer of the two-layer SVRMs, 180 samples for each condition were acquired for training and testing, 90 samples were used for training, and the remaining 90 samples were used for testing. In the second layer, there were 30 training samples and 30 testing samples for each fault severity. In the _rst layer, the inner race, outer race, ball fault, and bearing health target values were artificially set at 1, 2, 3, and 4, respectively, during the training while the actual fault sizes were determined as the target values in the second layer Shen [27].

The results obtained using experimental signals have come consolidate the conclusions reached in the case of simulations.

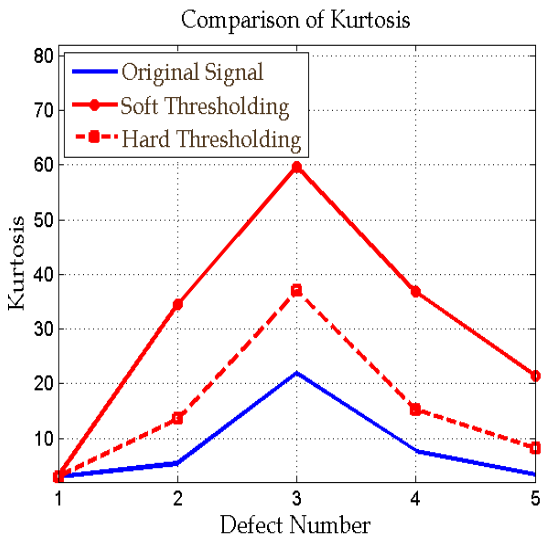

Figure 10. Comparison of original and reconstructed signals (Kurtosis)

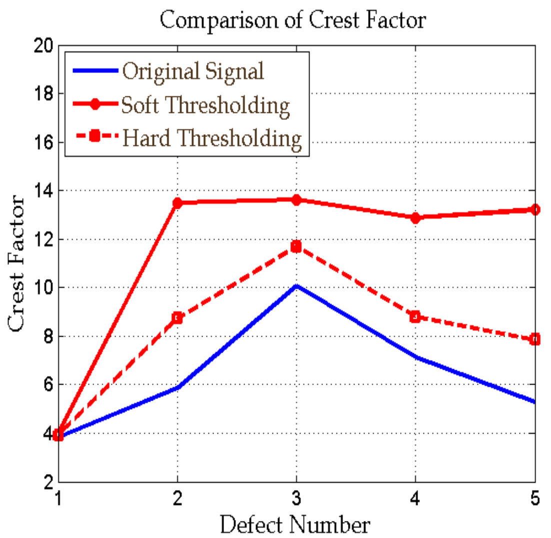

Figure 11. Comparison of original and reconstructed signals (Crest factor)

6. Conclusion

The wavelet transform is widely used for analyzing non-stationary vibration signals from rotating machines. The approach just described can trace the origin of some defects after decomposition of the original signal details and approximations. It allows removing the time invariant noise of a signal. This method improves thesensibility of temporal indicators such as the kurtosis and the crest factor which are often used in conditional maintenance by vibratory analysis. We can conclude that the technique based on the wavelet transform is an e_cient means for the diagnosis from rotating machines.

References

[1] A. Rai, S. H. Upadhyay, A review on signal processing techniques utilized in the fault diagnosis of rolling element bearings, *Tribology International*, 96, 2016, pp. 289-306.
[2] O. Rioul, M. Vetterli, Wavelets and signal processing, *IEEE signal processing magazine*, 8(4) , 1991, pp. 14-38.
[3] D. L. Donoho, De-Noising by Soft-Thresholding, *IEEE Transactions on Information Theory*, 41, 1991, pp. 613-627.
[4] G. A. Jimenez, A. O. Munoz, M. A. Duarte-Mermoud, Fault detection in induction motors using Hilbert and Wavelet transforms, *Electrical Engineering*, 89(3), 2007, pp. 205-220.
[5] X. Chiementin, F.Bolaers, O. Cousinard, L. Rasolofondraibe, Early detection of rolling bearing defect by demodulation of vibration signal using adapted wavelet, *Journal of Vibration and Control*, 14(11), 2008, pp. 1675-1690.
[6] A. Djebala, N. Ouelaa, N. Hamzaoui, Detection of rolling bearing defects using discrete wavelet analysis, *Meccanica*, 91, 2008, pp. 339-348.
[7] A. Djebala, N. Ouelaa, N. Hamzaoui, L. Chaabi, Detecting mechanical failures inducing periodical shocks by wavelet multiresolution analysis. Application to rolling bearings faults diagnosis, *Mechanics*, *58*(2), 2016, pp. 44-51.
[8] D. Wang, Q. Miao, X. Fan, H. Z. Huang, Rolling element bearing fault detection using an improved combination of Hilbert and Wavelet transforms, *Journal of Mechanical Science and Technology*, 23, 2009, pp. 3292-3301.
[9] C. Tang, Q. Miao, M. Pecht, Rolling element bearing fault detection: Combining energy operator demodulation and wavelet packet transform, *In : Prognostics and System Health Management Conference (PHM-Shenzhen)*, 2011. IEEE, 2011. pp. 1-6.
[10] P. G. Kulkarni, A. D. Sahasrabudhe, Application Of Wavelet Transform For Fault Diagnosis of Rolling Element Bearings, *International Journal of Technology Enhancements and Emerging Engineering Research*, 2(4), 2013, pp.138-148.
[11] M. AL-Tobi, K. F Al-Raheem, Rolling Element Bearing Faults Detection, Wavelet De-noising Analysis, *Universal Journal of Mechanical Engineering*, 3, 2015, pp. 47-51.
[12] D. S. Shaha, V. Patel, A Review of Dynamic Modeling and Fault Identifications Methods for Rolling Element Bearing, *Procedia Technology*, 14, 2014, pp. 447-456.
[13] Y. T. Sheen, A complex filter for vibration signal demodulation in bearing defect diagnosis, *Journal of Sound and Vibration*, 276, 2004, pp. 105-119.
[14] A. Bhende, G. Awari, S. Untawale, Assessment of bearing fault detection using vibration signal analysis, *Technical & Non-Technical Journal of Visual Soft Research Development*, 2, v, pp. 249-261.
[15] D. L. Donoho, L. M. Johnstone, Ideal spatial adaptation by wavelet shrinkage, *Biometrika*, 81, 1994, pp. 25-455
[16] D. L. Donoho, De-noising by soft-thresholding, *IEEE transactions on information theory*, 41(3), 1995, pp. 613-627.
[17] I. M. Johnstone, B. W. Silverman, Wavelet threshold estimators for data with correlated noise, *Journal of the royal statistical society: series B (statistical methodology)* 59(2), 1997, pp. 319-351.
[18] S. Chang, Y. Kwon, S. Yang, I. J. Kim, Speech Enhancement for non-stationnary noise environment by adaptive wavelet packet, *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing ICASSP '02*, 1, 2002, pp. 561-564.
[19] R. Kumar, P. Pate, Signal denoising with interval dependent thresholding using DWT and SWT, *International Journal of Innovative Technology and Exploring Engineering*, 6, 2012, pp. 2278-3075.
[20] P. D. Jena, S. N. Panigrahi, Gear fault diagnosis using bispectrum analysis of active noise cancellation based filtered sound and vibration signals, *International Journal of Acoustics and Vibration*, 18, 2013, pp. 59-70.
[21] N. Tandon, A comparison of some vibration parameters for the condition monitoring of rolling element bearings, *Measurement*, 12, 1994, pp. 285-289.
[22] C. Pachaud, Crest factor and kurtosis contributions to identify defects inducing periodical impulsive forces, *Mechanical Systems and Signal Processing*, 11, 1997, pp. 903-916.
[23] J. P. Dron, F. Bolaers, L. Rasolofondraibe, Improvement of the sensitivity of the scalar indicators (crest factor, kurtosis) using a denoising method by spectral subtraction: application to the detection of defects in ball bearings, *Journal of Sound and Vibration*, 270, 2004., pp. 61-73.
[24] M. Merzoug, K. Ait-Shgir, A. Miloudi, J. P. Dron, Improvement of the Sensitivity of the Scalar Indicators Using a De-noising Method by Wavelet Transform. *In Applied Mechanics, Behavior of Materials, and Engineering Systems. Springer International Publishing*. 2017, pp. 239-250.
[25] K. A. Loparo, Case western reserve university bearing data center, 2012.
http:csegroups.case.edu/bearingdatacenter/home.
[26] C. Shen, D. Wang, Y. Liu, F. Kong, P. W Tse, Recognition of rolling bearing fault patterns and sizes based on two-layer support vector regression machines, *Smart Structures and Systems*, 13(3), 2014, pp. 453-471.