Extraction of vibration signal parameters by DWT for a new approach to using Kurtosis

Aimé Joseph OYOBE OKASSA, Colince WELBA, Jean Pierre NGANTCHA

Abstract— **Production systems are largely made up of rotating machines. These rotating machines generate vibrations. These vibrations are important sources of information related to the functioning of the machine. In this work, we extracted the statistical parameters of a vibratory signal from the ball bearing. The parameters extracted are the standard deviation and the Kurtosis. To do this, we first extracted the two parameters for the time signal. The same time signal is then decomposed by DWT. The coefficients obtained are separated into approximation and detail signals. For each of the two signals we extract the standard deviation and the Kurtosis. These parameters were used to make the decision on the proper functioning of a ball bearing. The method was tested on a signal from a ball bearing in good condition and on the one with defaults. The test showed that the Kurtosis calculate from the approximation signal has the advantage of reducing the amount of data to be manipulated and giving less false alarm.**

Key Word: DWT, Maintenance of rotating machines, vibration signals, Kurtosis.

I. INTRODUCTION

In the industrial world, all rotating machines generate vibrations. A vibration is a reaction to rotating forces as well as friction forces occurring inside the machine.

The analysis of these vibrations, allows us to diagnose the inside of the machine without stopping it. Of all the measurable parameters in the industry without disruption of production, the one that contains the most information is the vibratory signature [1]. The evolution of vibration levels and the low efficiency of rotating machines are often due to a defect in the bearing or gears. Depending on the type and state of functioning of the machine, maintenance consists of establishing a monitoring method to verify the proper functioning of the internal components of industrial machines. The most well-known monitoring and diagnostic techniques are vibration, temperature, acoustic emission and oil film resistance monitoring. Among them, vibration measurement and monitoring are the most used and most effective means to monitor rotating machines. Several works have been done in the field to improve the preventive maintenance of rotating machines. For example, R. Chaib et al. presented a study on the monitoring of bearings by vibration analysis. The purpose of this work is the detection of early deterioration of a bearing by the use of a temporal statistical defect indicator which is kurtosis [2]. Keltoum Herrouz et al., presented a work based on monitoring by vibration analysis applied to an asynchronous motor. This work is intended for the early detection and diagnosis of failures on a rotating machine [3]. Jardine introduced decision models for determining revision intervals through reliability and cost analysis [4]. Cavacece et al., used the power spectrum to detect defects at an early stage in aeronautical transmissions [5]. Minnicino et al., used Hilbert transform to detect and diagnose rotating machine defects [6]. Pusey and Roemeront provided an overview of the development of diagnostic and prognosis in high-performance technologies for turbomachinery [7]. Basile developed a statistical approach to establish a reliability law for equipment. This approach is based on feedback [8]. Vachtsevanos et al., defined and described fault diagnosis by the artificial intelligence method and systems engineering fault prediction approaches through examples [9]. Other authors have compressed the vibratory signals. The overall aim of their work is to optimize the storage space of vibratory data for future exploitation or to optimize the bandwidth for their transmission [10], [11], [12].

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Despite the abundance of work in a very current field such as vibratory analysis, the method of processing vibratory signals based on the Wavelet Transform associated with a statistical method based on the Kurtosis, for the detection of early deterioration of a bearing has not yet been proposed on the vibration signals. The originality of this work lies in the improvement of the detection of the least variability of the amplitude of the vibratory signal by the use of wavelets.
This article consists of three parts: the state of the art, methodology, analysis and interpretation of the results.

II. STATE OF ART

A. *Generalities on vibratory signal processing*

The purpose of extracting statistical parameters from a vibration signal is to improve the observation of rotating machines. The conclusions drawn from the reading of these various parameters make it possible to conclude on the state of the rotating machines. Several methods were used to extract the parameters from the vibration signals.

The methods of the Statistical Indicators, historically the oldest, consist in an analysis of the temporal characteristics of the recorded signal. It typically contains the RMS (root mean square) value which measures the average energy of the signal, the peak-to-peak value which measures the maximum amplitude between the extreme values of the signal, the kurtosis which measures the impulsive character of the signal, etc. The implicit idea, when these indicators are used for monitoring and diagnosis, is that any appearance of a defect results in a significant change in the statistical characteristics of the signal [13], [14]. The advantages of time-based statistical indicators are their simplicity, their ease of interpretation and the possibility of supplementing them with thresholds whose exceedance triggers an alarm in an abnormal situation.

They are therefore particularly well suited for online and even real-time monitoring and control. However, these descriptors often generate "false alarms" when the signals are not Gaussian. Beyond these indicators some mathematical tools were used. Fourier analysis consists of breaking down the energy of the signal analyzed by frequency bands. This results in a finer analysis than the RMS value analysis, with the possibility of dissociating in the frequency domain independent phenomena characterized by different frequency blooms. Frequency domain analysis is the indispensable counterpart of signal temporal domain analysis. It is not uncommon for phenomena which are difficult to discern in one area to appear clearly in the other. Finally, Fourier's analysis has remarkable properties that make it an indispensable tool for carrying out numerous treatments. Fourier's analysis is particularly well suited to the monitoring and diagnosis of rotating machines whose signals distribute their energy on harmonics well localized in frequency. The amplitude and position of these harmonics constitute a real «mechanical signature» of the state of the machine.

Despite its many advantages, a major disadvantage of the Fourier analysis is that it assumes stationary signals, which does not allow to associate with a frequency signature the time interval where it occurs. In order to reconcile the concepts of time and frequency, time-frequency analysis is used. The aim is to characterize non-stationary signals in the frequency domain, for example those whose characteristics vary over time.

B. The Dimensional Indicators

Effective Value

The effective value is given by equation (1).

$$V_{RMS} = \left[\frac{1}{N}\sum_{i=1}^{N}(x_i^2)\right]^{1/2} \tag{1}$$

x_i is the sample of rank i;

N is the number of samples of the signal.

The effective value (V_{RMS}) allows you to quickly check the state of the machine and to indicate whether the operating conditions have changed in a worrying way since the last measurement. This criterion does not change significantly during the 1st degradation phase; it only begins to grow during the 2nd degradation phase [2]. This is a weakness for conditional maintenance and makes early detection not possible. In addition, the vibratory signal collected by the sensor always contains noise not only from the machine but also from the environment, which can lead to a misinterpretation of the RMS value.

Peak Value

The peak value is given by equation (2).

$$V_C = 20\log\left(\frac{A_m}{\sigma_x}\right) \tag{2}$$

σ_x - Standard deviation of the signal;

A_m - Maximum signal amplitude.

The peak value is an indicator that characterizes the maximum amplitude of shocks. It manifests itself from the appearance of the first flaking and gives very early information of the prediction. Unfortunately, this is a bad indicator once the degradation escalates.

Kurtosis

Kurtosis is defined by equation (3).

$$K = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i-\bar{x})^4}{\sigma_x{}^4} \tag{3}$$

$\bar{x}$ -Signal average.

Kurtosis is a non-dimensional indicator used to characterize the degree of flattening of a vibration signal distribution [2]. It has the advantage of being independent of the variations in the speed of rotation and the stresses suffered by the machine. Also, the vibratory signal of a bearing in good state generates a Gaussian distribution signal with a kurtosis around 3 within this range [2.75; 3.25] [15]. The detection of an early defect produces a transient and periodic signal with a modified distribution speed with a larger kurtosis. To quantify this change in distribution, kurtosis is the most sensitive factor.

III. PROPOSED METHOD

A. Parameter of Extraction Procedure

The proposed methodology is presented in Figure 1.

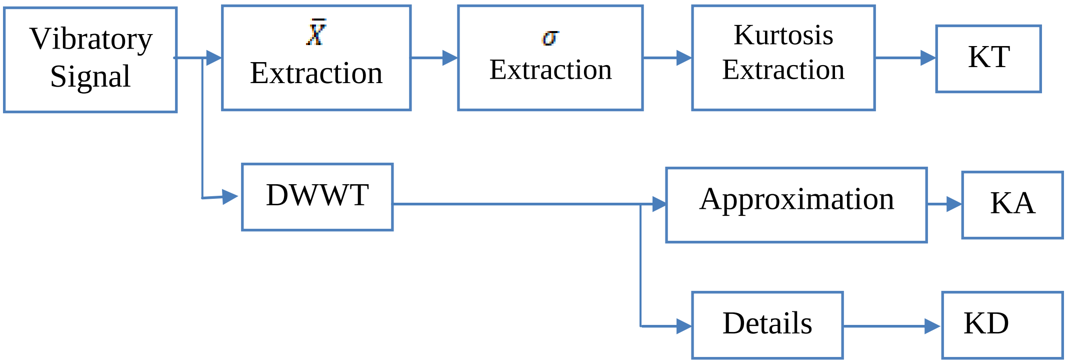

Figure 1 Parameter extraction diagram

Figure 1 shows the proposed algorithm for extracting parameters from vibratory signals. Vibration data is processed in parallel in both branches of the algorithm. In the first branch, the temporal mean (MT), the temporal standard deviation (sigmaT) and the temporal Kurtosis (KT) are calculated successively. In the second branch, the data are decomposed by the Discrete Wavelet Transform. One of the signals is the approximation signal. This approximation signal makes it possible to extract the mean MA, the standard deviation sigmaA and the kurtosis KA. The other signal is the detail signal. The detailed signal allows the extraction of the mean MD, the standard deviation sigmaD and the Kurtosis KD. These parameters are recorded in Table 1.

B Wavelet Decomposition Procedure

In mathematics, a wavelet Ψ is a square-integrable functions from the space of Hilbert $L^2(\mathbb{R})$, most often oscillating and zero-averaging, chosen as a multi-scale analysis and reconstruction tool. We define a family $\psi_{s,\tau}$ where $(s,\tau) \in \mathbb{R}^{+*} x \mathbb{R}$ of wavelets from the mother wavelet Ψ:

$$\forall t \in \mathbb{R}, \psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right) \quad (4)$$

To analyze a square-integrable function in wavelets consists in calculating all its scalar products with the wavelets family. The resulting numbers are called wavelet coefficients, and the operation associating its wavelet coefficients to a function is called wavelet transform. The continuous wavelet transform of a function$f \in L^2(\mathbb{R})$ is defined by:

$$g(s,\tau) = \int_{-\infty}^{+\infty} f(t)\psi_{s,\tau}^{*}(t)dt \quad (5)$$

For compression applications the Discrete Wavelet Transform (DWT) is used. This transformation is defined by the following equations:

$$a[j-1,k] = \sum_{k=1}^{n} h[n-2k]a[j,n] \quad (6)$$

$$d[j-1,k] = \sum_{k=1}^{n} g[n-2k]a[j,n] \quad (7)$$

$$H[\omega] = \sum_{k=1}^{n} h[k]e^{-jk\omega} \quad (8)$$

$$G[\omega] = \sum_{k=1}^{n} g[k]e^{-jk\omega} \quad (9)$$

In the equations (6), (7), (8) and (9) G [ω], H [ω], a [j-1, k], d [j-1, k] are respectively the low pass filter, the high pass filter, the approximation coefficients and the detail coefficients.

The reconstruction of the signals is done by equation (10).

$$a[j,k] = \sum_{n}^{N} h[n-2k]a[j-1,k] + \sum_{n}^{N} g[n-2k]a[j-1,k]$$

C. Analysis and interpretation of results

The method presented in this article has been implemented on two real vibratory signals. A first signal generated by a good bearing and a second signal generated by an used bearing. These two bearings have the same part number SKF7309B. Thus, these signals are recordings of the vibration monitoring of the ball bearing. The acquisition system consists of a portable collector, VIBROTEST 60 and an accelerometer. The signals were acquired with a sampling frequency of 2 kHz. The Acquisition Device model uses a 12-bit CAN. The vibratory parameter chosen for this work is the amplitude variation. The results of this implementation are recorded in Table 1.

Table 1 Functioning parameters of the two bearings

	Parameters in time space			Parameters in wavelet space					
	MT	sigmaT	KuT	MA	sigmaA	KuA	MD	sigmaD	KuD
Ball bearing Used	0.013	1.74	10.8	0.018	3.84	3.99	0.003	1.37	27
Ball bearing In good state	0.002	0.539	0.032	0.003	5.27	10.3	0.006	6.85	4.98E-3

Table 1 presents the results obtained with our algorithm. The standard deviations (sigma) obtained in time space with both signals show that the dispersion is greater with the signal generated by the worn ball bearing. This means that there is the appearance of random values in the signal (expression of the malfunction of the ball bearing). The temporal Kurtosis of the signal generated by the worn ball bearing is greater than the reference value three (3). In the literature the kurtosis of a ball bearing in good condition is between –3 and +3. This result obtained with the worn ball bearing confirms what we know: the ball bearing is worn. The standard deviation of the sub-band signal approximation of the wavelet space is greater than that of the signal in the time space for the ball bearing in good condition. This order remains true for the worn ball bearing. In each case, the standard deviation of the data in time space is smaller than that of the wavelet space data. This is justified by the great power of data bleaching that wavelets possess. Indeed, decorrelated data are highly dispersed than those not decorrelated. The Kurtosis value of the data in the space of the approximations is higher than that of the Kurtosis in the time space. This analysis allows us to conclude that for the reading of the parameters for assessing the proper functioning of the ball bearing, we must check whether the value of Kurtosis in the approximation space is beyond the interval [-3; +3]. The approximation signal is a signal stripped of the detail signal, often consisting of tolerances of ball bearing manufacturing processes. Thus, tracking the function of a ball bearing by the approximation signal can prevent early alarms. The decimation of the data during the wavelet decomposition reduces the size of the window to be processed. This reduction solves storage problems, the computational load and improves the detection threshold for malfunctions. However, the Kurtosi of the time and detail signals of the worn ball bearing are high and exceed the values of the reference interval. The justification for this result is that the values of the detail signal often experiment large frequency variations, which increases the value of the kurtosis of the detail signal. This result is not important because the detail signal is a non-essential signal for this analysis. On the observation screen, signal processing for serviceable and malfunctioning ball bearings is shown in Figures 2 and 3, respectively.

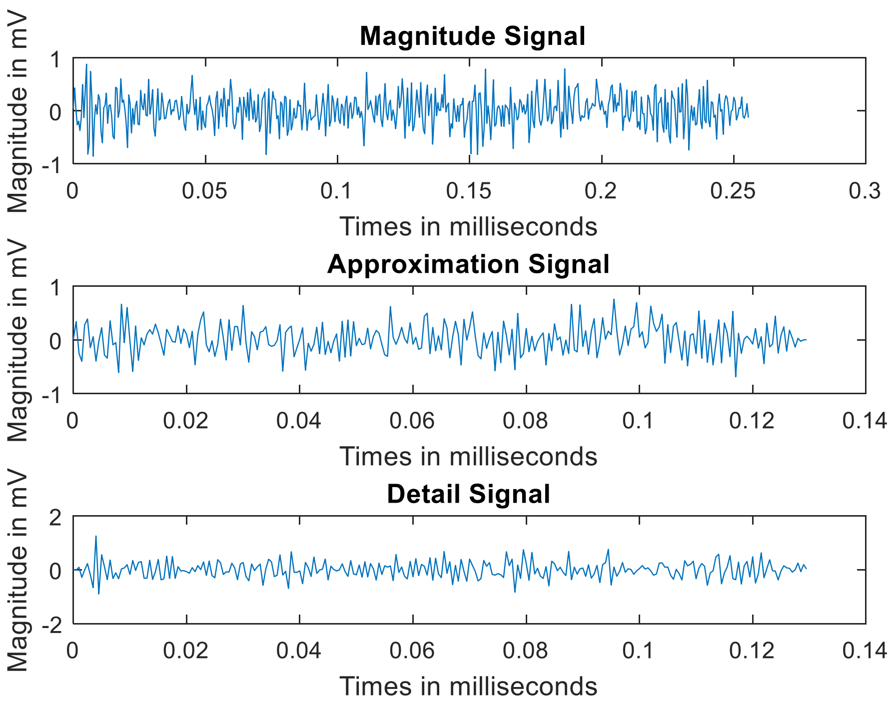

Fig. 2. Reference Bearing Signal Processing

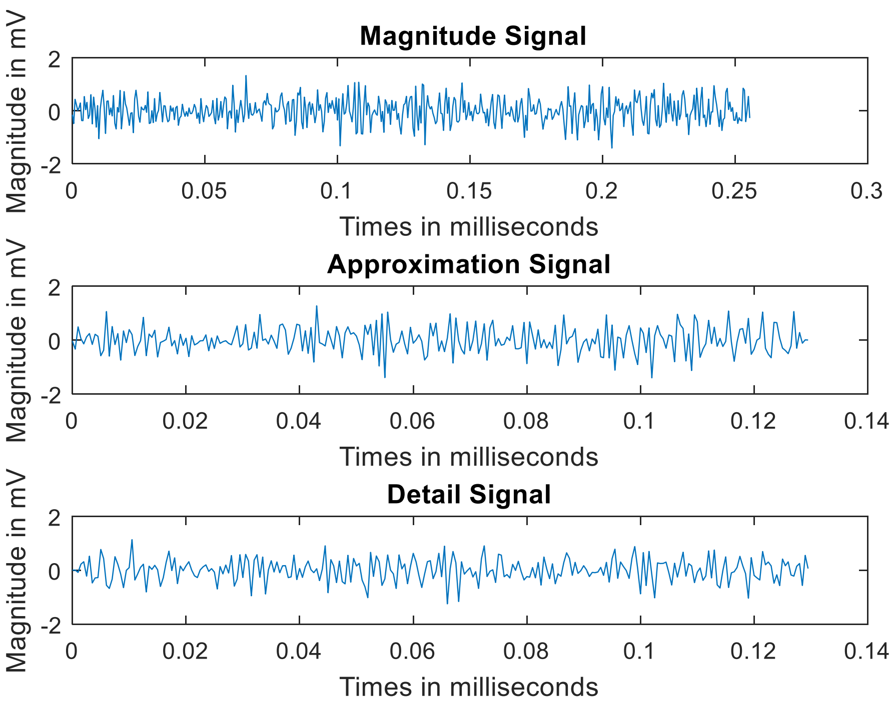

Fig. 3. Treatment of the Worn Ball Bearing Signal

Figures 2 and 3 are the results that appear on the screen. It is difficult to assess the state of a bearing simply by looking at the two figures. However, a careful look shows the increase in the amplitude of the vibration for the worn ball bearing.

IV. CONCLUSION

In this article, we presented a method of monitoring the proper functioning of a ball bearing by its vibratory signature. Table 1 shows that an opinion on the functioning of a ball bearing can be given by reading its Kurtosis. The method we propose will have the advantage of avoiding false alarms. In fact, the isolation of the signal details, often made up of different manufacturing tolerances, allows keeping only the events that occurred during the functioning of the ball bearing. This has significantly improved the threshold for alerts. Also, the decimation of the data during the wavelet decomposition allowed the reduction of the data of the processed window; this has the effect of the reduction of the computational load of the algorithm. The results obtained are compared with those obtained with the reference ball bearing. This comparison is encouraging.

However, after a state of the art on data extraction methods, we can think that there would exist a filter that would play the role of the wavelet to allow calculating this Kurtosis in the same space.

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