Analysis of vibration signals using cyclostationary indicators

Georges ISHAK[1], Amani RAAD[1] and Jérome ANTONI[2]

[1]Ecole doctorale de sciences et de technologie, Université Libanaise, Liban,

[2]INSA de Lyon, France.

{georges.ik@hotmail.com, amaniraad@hotmail.com,jerome.antoni@surveillance7.fr}.

Abstract

The purpose of this paper is to take advantage of the cyclostationary indicators, in order to detect and classify the defects that can occur on mechanical parts of a system, such as the gearboxes and the bearings.

The set of data used includes a variety of signals that describe the healthy state of a bearing, as well as other faulty states. After resampling the signals in the angular domain, a synchronous averaging is then performed in order to calculate the second, third and fourth order cumulants. The calculated cumulants, in addition to the first order moment, are the tools needed to calculate the cyclostationary indicators. Those indicators will be used as input parameters for an artificial neural network, in order to lead to an efficient fault detection and classification, with a high accuracy, and using the minimum number of parameters.

This paper offers for the first time, the analysis of bearing signals using higher-order cyclostationary indicators up to the fourth order. Moreover, it permits to test how powerful would be the cyclostationarity indicators when used with an artificial neural network, as this kind of parameters is not typically used in the previous mechanical fault classification procedures.

1 Introduction

During the latest years, cyclostationarity has shown a big interest in the study of rotating elements, since those elements can carry some hidden periodicities during their rotation. Since 1991, many descriptors have been proposed to calculate the degree of cyclostationarity, starting with ZIVANOVIC and GARDNER [1]. In 2005, RAAD and al [2] have proposed some new cyclostationarity indicators that can be extended till the fourth order. Those indicators have been tested on healthy and faulty gear signals, and have shown a significant efficiency when it comes to the fault detection using a predefined threshold. Bearing signals have never been tested with this kind of indicators, as well as the effectiveness of these indicators when used with an artificial neural network.

The following sections show the results obtained when implementing those indicators (proposed by [2]) on healthy bearing signals, as well as on faulty signals that come from inner race faults, outer race faults or rolling element faults. Once the indicators have been generated, the signals are classified using an artificial neural network, with exact radial basis activation functions.

2 Cyclostationary analysis

2.1 Generalities about cyclostationarity

Vibration signals, especially those extracted from rotating machines, are non-stationary signals that present in their background some hidden periodicities. To extract those periodicities, it is possible to use many

tools of signal processing. One of the powerful tools is the cyclostationary analysis.

In a first approach, a non-stationary signal is said to be wide sense cyclostationary if its autocorrelation function $R(t,\tau)$ presents many periodicities with respect to time t, in opposite with the stationary signal whose autocorrelation function is periodic with respect to the time lag τ[3].

$$R(t+T,\tau) = R(t,\tau) \quad (1)$$

Where $R(t,\tau) = E\{x(t)\, x(t-\tau)\}$

Similarly, a non-stationary signal is said to be nth order cyclostationary with a cyclic period T, if its nth order moment is periodic of period $\tilde{T}$. [4]

$$m_{(n)}(\tilde{t}) = m_{(n)}\big(\tilde{t} + \tilde{T}\big) \quad (2)$$

Where $\tilde{T} = [T, T, \dots, T_{(n)}]^t$and $\tilde{t} = \big[t, t, \dots, t_{(n)}\big]^t$

A pure cyclostationary signal is an n^{th} order cyclostationary signal, whose all cyclostationary contribution of the lower orders is extracted. This operation requires checking the periodicities of the cumulants related to the vibration signal [5]. The cumulants are calculated after extracting the synchronous average.

2.2 Cyclostationary indicators

The use of cyclostationary indicators has shown a big interest many years ago. Since 1975, many contributions were developed to measure the degree of cyclostationarity. The indicators that were developed by RAAD and al were tested on gear signals, their evolution was determined with respect to the severity of the gear fault. Those indicators have shown some significant results (detail some results from the paper). They had many advantages:

- They are monotonic increasing functions of the degree of cyclostationarity.
- They are theoretically null for a stationary signal.
- They are normalized by the signal’s energy and have no dimension.
- They generalize some standard cumulants like the RMS value, the skewness, and the kurtosis, giving them a cyclic signification.

A signal $x(t)$ is defined by its first order moment $m_{1x}(t)$, and its cumulants of higher orders $c_{2x}(t,\tau)$, $c_{3x}(t,\tau_1,\tau_2)$, and $c_{4x}(t,\tau_1,\tau_2,\tau_3)$. The cyclic moment M_{1x}^{α} and cumulants C_{nx}^{α}, are defined to be the Fourier coefficients of the temporal moment and cumulants[2].

$$C_{2x}^{\alpha}(0) = \int S_{2x}^{\alpha}(f)df \tag{3}$$

$$C_{3x}^{\alpha}(0) = \int S_{2x}^{\alpha}(f_1, f_2)df_1 df_2 \tag{4}$$

$$C_{4x}^{\alpha}(0) = \int S_{2x}^{\alpha}(f_1, f_2, f_3)df_1 df_2 df_3 \tag{5}$$

S_{2x}^{α} being the spectral correlation function at the cyclic frequencies.

The indicators that were proposed up to the fourth order were given as follows [2]:

$$I_{1x} = \sum_{\alpha\neq 0} |m_{1x}^{\alpha}|^2 \tag{6}$$

$$I_{2x} = \sum_{\alpha\neq 0} |C_{2x}^{\alpha}(0)|^2 \tag{7}$$

$$I_{3x} = \sum_{\alpha\neq 0} |C_{3x}^{\alpha}(0{,}0)|^2 \tag{8}$$

$$I_{4x} = \sum_{\alpha\neq 0} |C_{4x}^{\alpha}(0{,}0{,}0)|^2 \tag{9}$$

After normalization of these indicators by the signal energy, we lead to the following relations[2]:

$$I_{1x}^{n} = \frac{I_{1x}}{|C_{2x}^{0}(0)|} \tag{10}$$

$$I_{2x}^{n} = \frac{I_{2x}}{|C_{2x}^{0}(0)|^2} \tag{11}$$

$$I_{3x}^{n} = \frac{I_{3x}}{|C_{2x}^{0}(0)|^3} \tag{12}$$

$$I_{4x}^{n} = \frac{I_{4x}}{|C_{2x}^{0}(0)|^4} \tag{13}$$

In general, cyclostationary indicators are calculated on angular sampling signals. If this sampling is not possible, angular resampling helps getting a fixed number of samples over one machine turn; therefore, the vibration signal becomes related directly to the position of the machine shaft, and the same for the periodicities. The extraction of cumulants becomes more accurate in this case.

3 Signals

3.1 Database

The tested signals were acquired at the University of New South Wales (UNSW) in Australia. The database contains gear and bearing signals. The gear signals are divided into healthy and faulty ones. The bearing signals refer to healthy bearings, bearings with inner race faults, outer race faults, and rolling element faults, with a zero degree contact angle, each fault being alone. The bearing faults are of the form of a localized and reduced size spalling. Other signals also contain hybrid faults gear/bearing.

All the signals are acquired upon two rotation speeds 6 Hz and 10 Hz (360 and 600 rpm). Four torque ratings are also available for each signal: 25 Nm, 50 Nm, 75 Nm and 100 Nm. All the signals are sampled with a 48 KHz sampling rate over 100 000 samples.

The accelerometer is placed right on the top of the faulty bearing which is located on the driven shaft. Two encoders of resolution 900 points per turn are placed on the driving and on the driven shafts. In addition to that, a once per revolution signal is obtained from the encoder on the driving shaft.

The bearings used along the tests are of the type Koyo 1250, they are self-aligning bearings with 12 balls on each column.

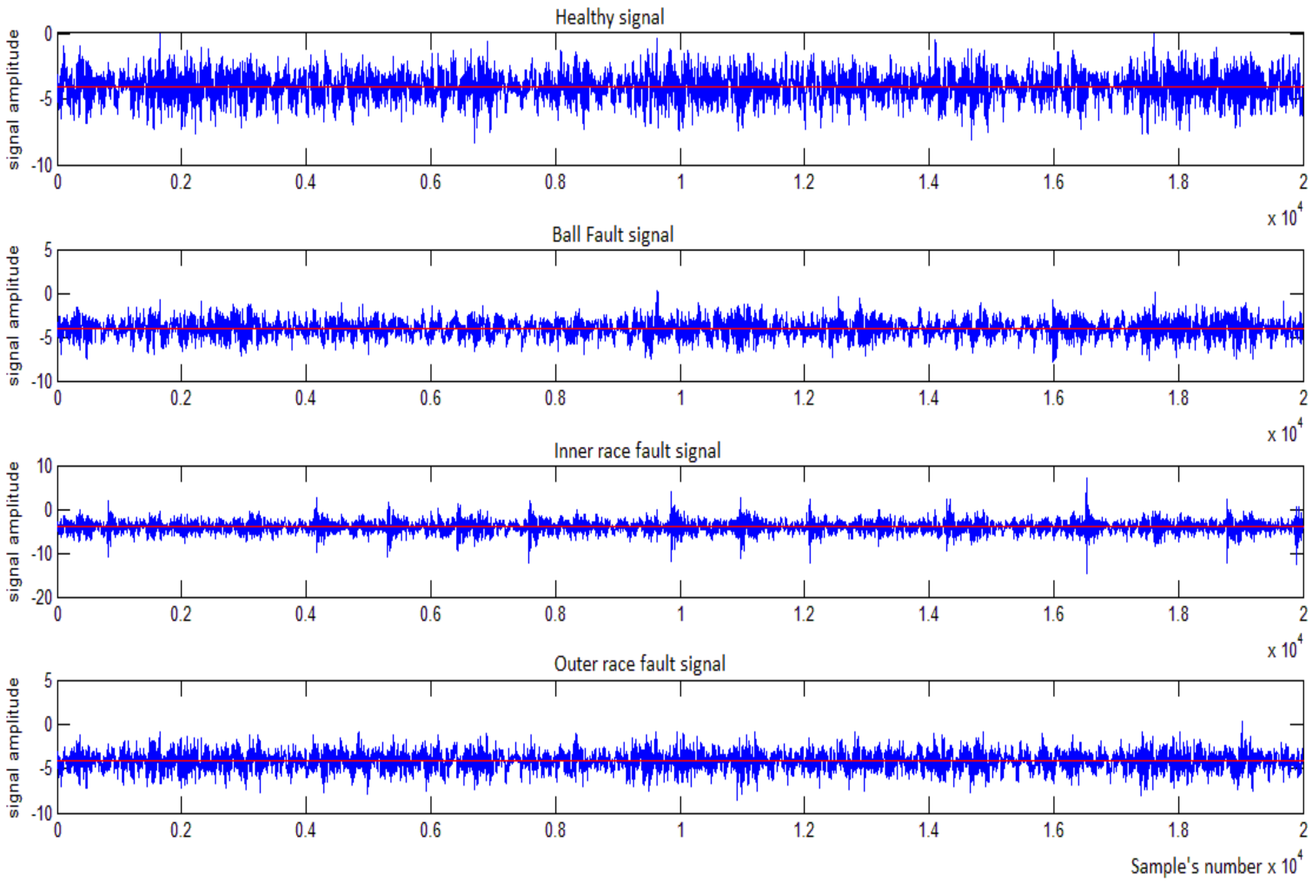

Figure 2: A set of signals presenting the different fault types at the rotation speed of 360 rpm

3.2 Data management

The set of data that was used contains the signals that describe the healthy state as well as the faulty state of a bearing for the two available speed rating and the four available torques. A total of 32 signals were used for this task.

As a first step, the signals were cropped on both sides to fit a certain well know number of cycles using the one per revolution signal of the encoder. Typically 12 complete cycles for the rotation speed of 360 rpm (~ 8000 samples per complete cycle), and 20 complete cycles for 600rpm (~ 4800 samples per complete cycle). Then the signals were resampled on an angular basis using the encoder signal that has a resolution of 900 points per turn. 20 points per encoder revolution were used so that the complete cycle will contain 18000 samples. The synchronous average was extracted from the signal in order to generate the cumulants.

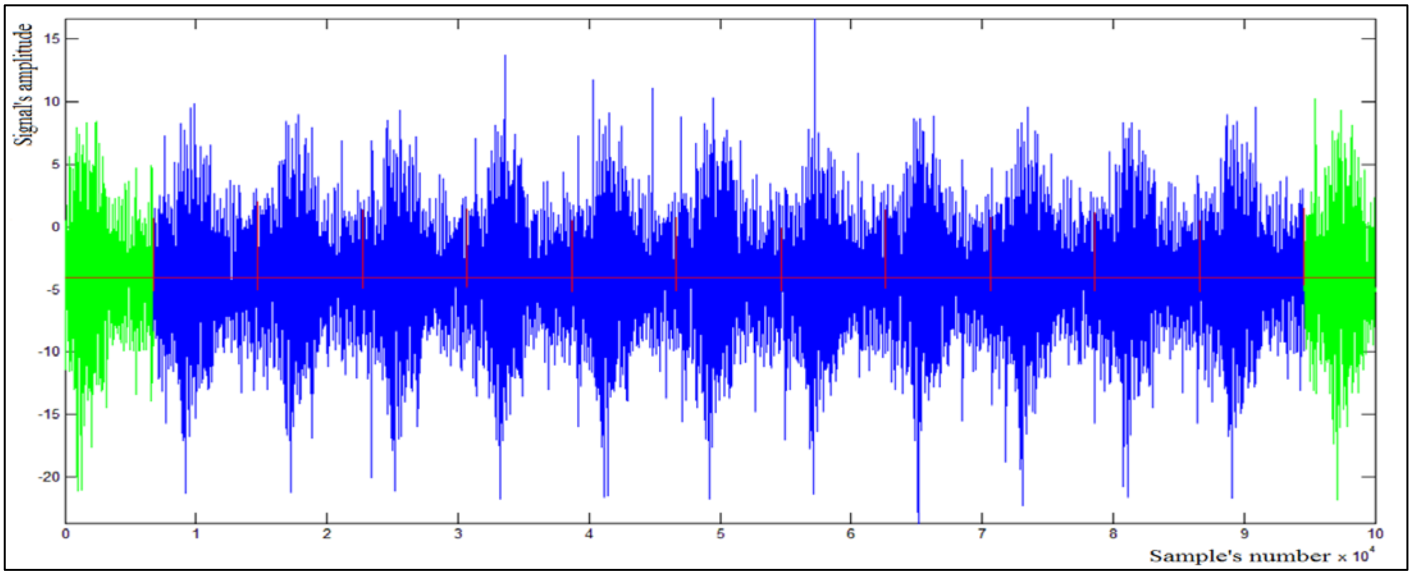

Figure 2: Cropping the signal edges using the once per revolution signal

3.3 Obtained results

After the signals are ready to be used, cyclostationary indicators have been calculated for each fault type. Figures 2 and 3 show the results. For the first and second order indicators, the contribution with the faulty state was very limited or absent. As for the higher order indicators, the contribution of the indicators with the faults was highly visible, and the faulty state can be directly identified using a simple threshold. The ball fault was the most to contribute with the higher order indicators; the inner race follows it, and finally comes the outer race fault. Moreover, every time the torque was increased, we could visibly see a diminution in the value of the indicators.

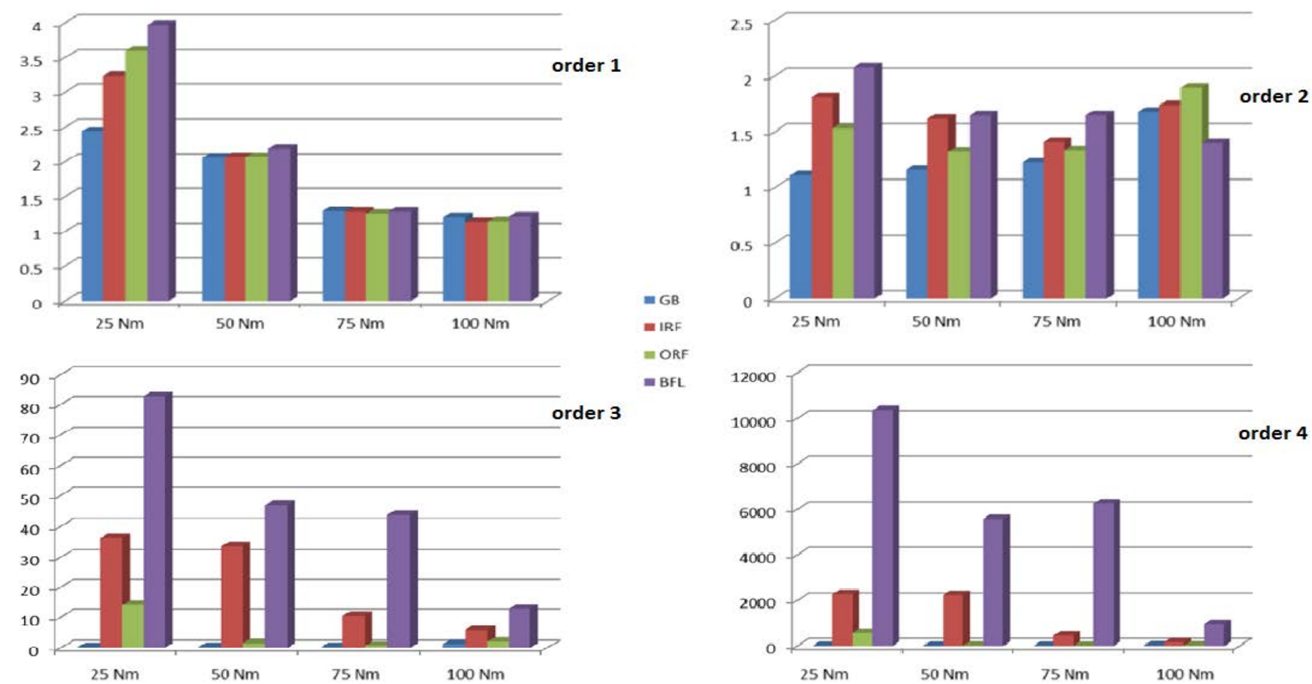

Figure 2: Cyclostationary indicators at the rotation speed of 600 rpm.

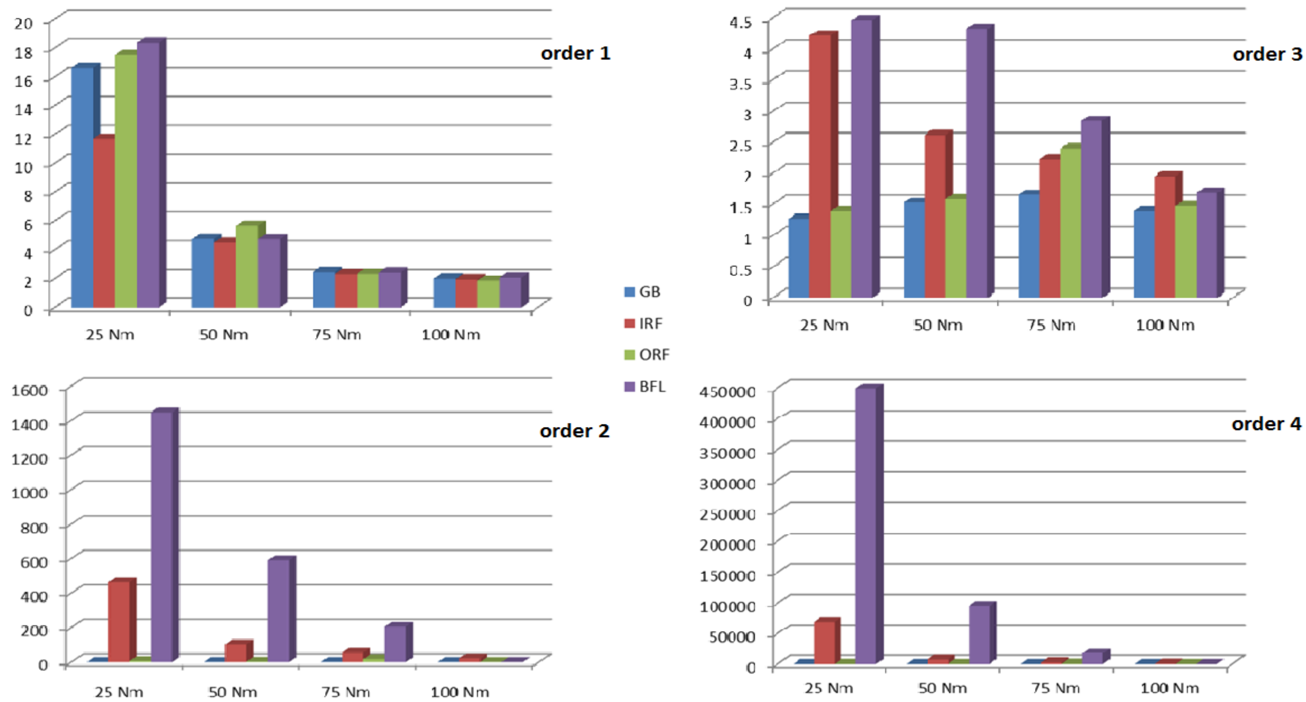

Figure 3: Cyclostationary indicators at the rotation speed of 360 rpm.

4 Artificial neural network

4.1 Learning

The automatic detection and classification of bearing defects was implemented on an artificial neural network of the type RBF exact, and using MATLAB®. The set of data that was used to teach and test the neural network comes from the signals that describe the bearing state with respect to the rotation speed and torque. The program was set to teach the neural network with a signal that has a length equal to ¾ to length of the original signal, and that's by taking randomly distinct cycles. This means for the 360 rpm rotation speed, as for the original signal we have 12 complete cycles, each time the program takes 9 cycles randomly from the original signal, calculates the cyclostationarity indicators, and teaches the neural network with a new set of data. 220 combinations of 9 cycles are possible. The same procedure is made for the 600 rpm rotation speed, where the program choses randomly 15 cycles of 20 to teach the neural network. 15504 combinations of 15 cycles are possible. All we used is 20 combinations to teach the neural network, and 20 others to test it, and that's for each signal. Those actions were repeated up to 10 times in order to assure the stability of the results, and average the global performance.

4.2 Fault detection and classification

The fault detection performance of the neural network was tested for two different cases, the case where the input parameters are the four cyclostationary indicators. And the other case is when only the higher order cyclostationarity indicators (third and fourth order) are used as input parameters. The performance results came as follows:

	Indicators first to fourth order	Indicators third and fourth order
performance	94.88%	93.97%

Table 1: Neural network's performance in bearing fault detection.

The same input parameters have been used to test the neural network's performance classifying the different bearing faults. The performance results came as follows:

	Indicators first to fourth order	Indicators third and fourth order
performance	93.97%	90%

Table 2: Neural network's performance in bearing fault classification.

Those indicators have shown an important performance when used with the artificial neural network; they are not only performing, but also fast to be computed. This can help realize many operations successively on the signal to insure whether the results are accurate or not. With a performance of 90%, and with a faulty signal, 5 repetitions are needed to get at least one correct result at 99.999%, and at least three correct results at 99.799%. It is a matter of seconds.

4 General conclusion

The mechanical faults caused by the bearing failure have shown a big influence on the evolution of the cyclostationary indicators that have been used in this paper. The advantage of the response received by those indicators resides mainly in their simple way to calculate, the task that can be accomplished in milliseconds on any computer that is not dedicated for heavy operations. Those indicators have been also proved to be powerful standalone input parameters for an artificial neural network. This performance might be improved if the artificial neural network is substituted by other means of the artificial intelligence. Other scenarios could also be discussed in further applications such that the presences of dual faults gear/bearing, or any other fault occurring simultaneously with the bearing one.

Acknowledgement

The authors would like to thank the Lebanese University for its support in this work.

References

[1] Zivanovic G., Gardner W., (1991). Degrees of cyclostationarity and their application to signal detection and estimation. Signal processing, 287-297.

[2] Raad A., Antoni J., Sidahmed M.(2005). Feature extraction using indicators of cyclostationarity for a mechanical diagnosis purpose. Computer assisted mechanics and engineering sciences, Vol.12, No. 2-3 :223-230.

[3] Bouillaut L., Sidahmed M.(1998). Approche cyclostationnaire et bilinéaire des signaux vibratoires d'engrenage, 3ème conf. inter. Méthode de surveillance, Senlis France, Vol. 1 : 323-332.

[4] Bonnardot F., (2004). Thèse : Comparaison entre les analyses angulaires et temporelles des signaux vibratoires de machines tournantes. Etude du concept de cyclostationnarité Floue, INPG, Grenoble.

[5] Gardner W., Spooner C. (1994). The cumulant theory of cyclostationary time-series, part II: Development and applications. IEEE Transactions on signal processing, Vol. 42, No. 12.