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MILLING CUTTING TOOLS DIAGNOSIS WITH HIGHER ORDER CYCLIC SPECTRA

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Abstract

This work presents a diagnostic method to detect faults in milling cutting tools. The proposed method is based on higher order cyclic spectra and is applied to vibration signals. HOS (higher order statistics) are defined in terms of moments and cumulants for the stationary case and HOCS (higher order cyclic statistics) are an extension to the cyclostationary case which characterizes the vibration signal of the rotating machines. The HOCS present an important property; as they enable the detection of the cyclostationarity and the bilinear links in the signal.
In general faults in rotating machines are often of a non linear nature, and increase the cyclostationary links in the vibration signals. In this paper, we use angular sampling to make the signals cylostationary. HOCS are estimated by using averaged cyclic biperiodograms. The experimental results based on vibration signals of a tool milling operation sampled in the angular domain show that the HOCS based method is linked to the tool state, i.e. faulty or good, and is able to detect, in the preliminary stage, different fault states, especially wear.

1. INTRODUCTION

The early identification of the tool wear and breakage in metal cutting operation is advantageous not only in terms of cost and catastrophe prevention, but also in terms of maximizing productivity.
Metal cutting is a complex non linear process because several factors affect this process, like cutting parameters, feed speed, cutting speed, workpiece geometry, tool state, etc. The tool wear and teeth breakage are the most encountered defects in such processes [1,2]. So many diagnostic approaches have been proposed using cutting forces, acoustic emission, accelerometers and other approaches [3, 4]. In this work, we are interested in analysing vibration signals taken from accelerometers. These vibrations are directly related to the complex dynamics of the structure and have a non linear behaviour. Tool wear and breakage affect the regime and generate more non linearity in the measured vibratory signal.

In tool monitoring control, different diagnostic methods have been proposed, such as HOS (especially bispectrum, bicoherence). HOS present some interests for chatter degree identification as it helps in quantifying the non linearity in the force signal [5]. In reference [6], HOS are also used as a basis of a classifier method for tool wear in circuit board assembly.

For rotating machines, the vibratory signal is cyclostationary if its periodic component is constant or if the signal is sampled in the angular domain [7]. Therefore their moments or cumulants (if they exist) are periodic in the time domain. The HOCS are good tools for characterising the different correlation links between signal harmonics [8] and they have the ability to indicate the presence of faults via the bilinear and cyclostationary links. In Practice, in spite of theses detectability properties, the cyclic bispectra (third order spectra) are rarely used in machine diagnosis since the signal must be cyclostationary.

This paper is organized as follows. In section 2, we introduce definitions and interpretation of the HOS, for both the stationary and cyclostationary cases. In section 3, the test rig is presented as well as the analysis of the experimental results. Finally, the conclusion and perspectives are given in section 4.

2. HIGHER ORDER AND HIGHER ORDER CYCLIC STATISTICS

2.1. Higher order statistics (HOS):

HOS can be calculated by extending the definition of the conventional second-order power spectrum. The power spectrum of a discrete time series *x(n)* can be presented by the signal's discrete Fourier transform (DFT) as:

$$S_{xx}(f) = E[X(f)X^*(f)] \tag{1}$$

where E [] denotes the expectation operator, f is the discrete frequency variable and * is the complex conjugate. The bispectrum can also be defined using the signal DFT as:

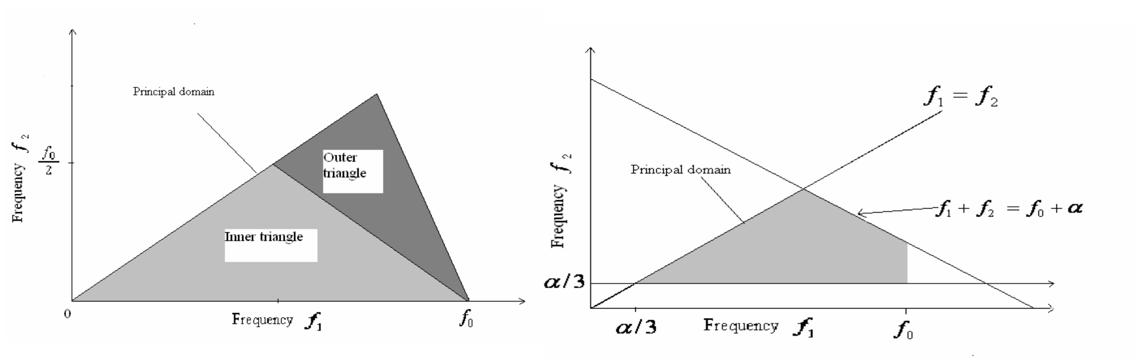
$$B_x(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1 + f_2)] \tag{2}$$

Note that the bispectrum as defined in formula (2) has two frequency indices f_1 and f_2 and is a complex function, so it preserves phase information, whereas the power spectrum defined in formula (1) is phase blind. The bispectrum allows the detection of both the deviation from normal distribution and the quadratic phase coupling [9]. Several symmetries exist in the (f_1, f_2) plane, so it is not necessary to compute $B(f_1, f_2)$ for all (f_1, f_2). The non redundant region, which is often called the principal domain (PD), is the only region of concern. The PD is defined in formula (3) and illustrated in figure (1-a):

$$\{(f_1, f_2) : 0 < f_1 < f_0, f_2 < f_1, f_1 + f_2 = f_0\} \tag{3}$$

where f_0 is the signal bandwidth.

In practice, the frequency components at f_1 and f_2 can be coupled for generating another component at $f_1 + f_2$. This interaction of f_1 and f_2 is called a quadratic phase coupling. Since the power spectrum suppresses all phase information, it cannot provide this relation. However, the bispectrum is capable of detecting and quantifying phase coupling.



(a) (b)

Figure 1. Principal domain (PD). (a) the stationary case, (b) the cyclostationary case for $\alpha > 0$.

2.2 Higher order cyclic statistics (HOCS):

Random sequences involved in communication and signal processing applications are often assumed stationary and ergodics. These assumptions are a mathematical idealisation of the real case and exclude a large interesting class of non stationary signals. Signals generated by mechanical systems exhibit some periodicities due to cyclic events. To highlight these cyclic events, signals are sampled in the angular domain. These types of signals are called cyclostationary signals and the use of the HOS tools on these signals is called higher order cyclic statistics (HOCS).

The HOCS and some estimators are defined by Dandawaté [10] in the frame of discrete time and continuous real signal, whereas Gardner [11] defined HOCS in the frame of fraction of time and applied these tools to communication signals [12]. In [13], an application of HOCS to gear diagnosis is given and the results are encouraging.

In this work, we apply the cyclic bispectrum to the vibration signals taken from a tool cutting machine. The vibration signals are sampled in the angular domain in order to make the signals cyclostationary.

Let *x(n)* be a cyclostationary signal, its HOCS can be formed by extending the cyclic spectral correlation. The cyclic spectral correlation of *x(n)* is defined as:

$$S_{xx}(\alpha, f) = E[X(f)X^*(f-\alpha)] \tag{4}$$

Where E[] denotes the expectation operator, *X(f)* is the discrete Fourier transform $\alpha = \frac{k}{T}$ (k=1… N) is the cyclic frequency values with T is the cyclic period. The cyclic bispectrum can be also described by:

$$B_{3x}^{\alpha}(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1+f_2-\alpha)] \tag{5}$$

As in the classic bispectrum, the cyclic bispectrum has a PD and the presence of the cyclic frequency in formula (5) modifies the PD from that earlier defined in formula (3). The new definition is given in formula (6) and is illustrated in figure (1-b):

$$\left\{(f_1, f_2) : \alpha/3 < f_1 < f_0 ; and ; f_2 < f_1 ; f_1 + f_2 = f_0 + \alpha\right\} \tag{6}$$

To estimate the bispectrum, we can use the sample estimator [12] given by:

$$\hat{B}_{3x}^{\alpha}(f_1, f_2) = \frac{1}{N} X_N(f_1) X_N(f_2) X_N^*(f_1 + f_2 - \alpha) \tag{7}$$

where N is the Fourier window length.
This estimator is unbiased and inconsistent. For instance if *x(n)* is a white cyclostationary process, the variance [10] of this estimator is $NS_{2x}^{0}(f_1)S_{2x}^{0}(f_2)S_{2x}^{0}(f_1 + f_2 - \alpha)$.
Nevertheless, it can be reduced either by using the averaged cyclic biperiodogram (temporal smoothed) or the smoothed cyclic biperiodogram (frequency smoothed) methods.
Here the first method is used as follows: the data record of length L is segmented into N_b blocks of length N which is equal to the length of each machine cycle operation. The synchronous average is calculated and subtracted from each block. In this manner only the information of order three remains.
The biperiodogram defined in formula (7) of each cycle raw is calculated for a given cyclic frequency α; that is only the triple product of the Fourier transform. All the biperiodgrams calculated are then averaged. The leakage effect is decreased by dividing each biperiodogram by the window effect. We get a good estimation of the cyclic bispectrum if the number of blocks $N_b > N$.
The cyclic bispectrum [8] combines two properties:

1. It detects the cyclostationary links between harmonics; these links give information about the faults. When a fault exists in the machine these links increase in the measured signal. For example, if one tooth is worn it will have a periodic impact which is different from the other teeth and will increase the cyclostationary links.
2. It detects and quantifies the nonlinearity asymmetry, as in the stationary case; due to that faults often generate quadratic coupling nonlinearity between harmonics.

3. EXPERIMENTAL RESULTS

3.1. Test rig:

A test rig to generate cutting data from a milling operation was prepared. Accelerometers (gain 100mv/g), were placed in three mutually perpendicular directions [x direction, y workpiece, z direction as shown in figure (2)]. An optical encoder to enable the angular sampling was installed in the spindle, (figure (2)). It delivers a position information (squared signal at frequency 2500*f_r, where f_r is the revolution speed) which is used as a clock for the data acquisition card. Therefore, signals were sampled at constant angle intervals.
For an optical encoder of a resolution equal to 2500 points per revolution, and an average speed of revolution f_r =10.833Hz, the average sampling frequency will be $f_s = f_r * 2500$. Nyquist frequency must be adjusted according to the instantaneous speed.

Experiments with the milling cutting tool were performed for one minute of milling. The face milling cutter had 5 unequally spaced teeth. The cutting parameters and the operating conditions were kept constant during the experiment (see table (1)).
In the experimental analysis, we have considered four tool cutting states: without fault, with a worn tooth (0.2mm), with two worn teeth (0.2mm) and with a broken tooth. All signals coming from the three axes[x, y, z] were tested. The best signal which has the highest vibration was the one from the accelerometer setting in the workpiece in y direction (see figure.2), so it will be used in our analysis.

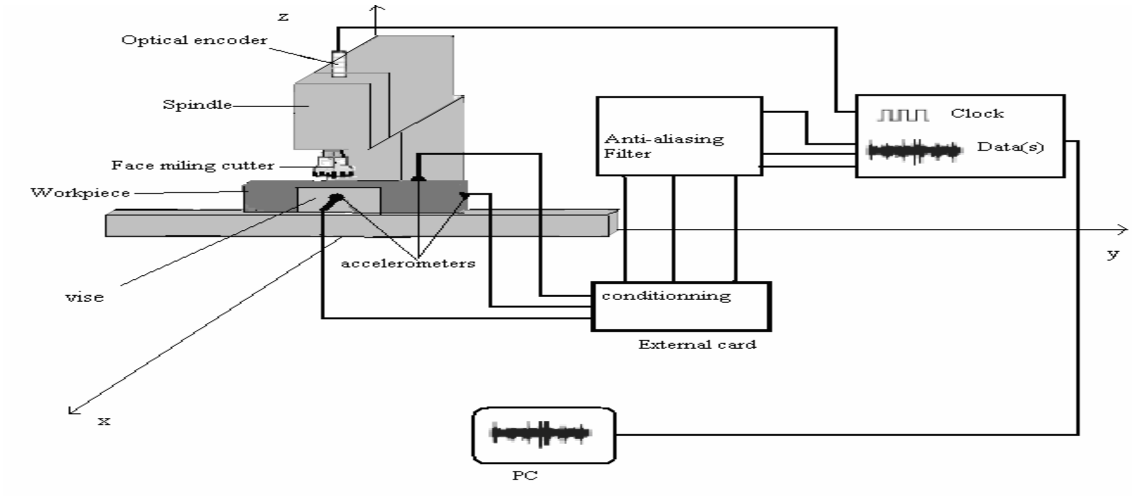


Figure 2. Schematic presentation of the experimental.

Material of the specimen	steel
Rotation speed	650 rpm
Feed rate	220 mm/min
Milling cutter diameter	100 mm
Teeth number	5
Cutting depth	0.7 mm
Optical encoder resolution	2500 point per revolution
Number of recorded cycles	500
Number of samples	1250000 samples
Averaged sampling rate	27 kHz
Anti-aliasing filter	9 kHz

Table 1. Cutting conditions and angular sampling parameters.

(a) Resonance frequencies (Hz)(fault free case)	502.5	819.9	1084	1375	2300	2777	3253
(b) Resonance frequencies (Hz) (two worn teeth case)	502.5	846.4	1137	1402	2354	2724	3227
Ratio : $(a-b)/a \times 100$	0	3%	4.6%	2%	3%	2%	1%

Table 2. Resonance frequencies in the fault free case and the worn teeth one

Figure (3) presents three cycles of the signal from this sensor for the fault free case. It shows the repetition of the five peaks which correspond to five teeth. The peaks' magnitudes are not equal due to unequally spaced teeth. This repetition shows the cyclostationary nature of the milling vibration signal taken under angular sampling.

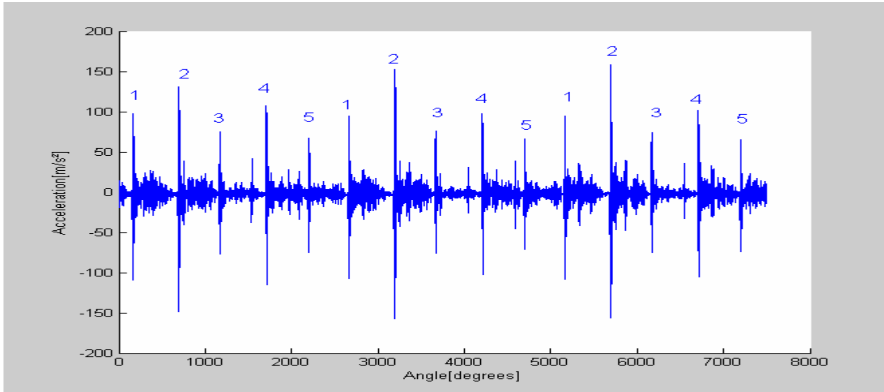
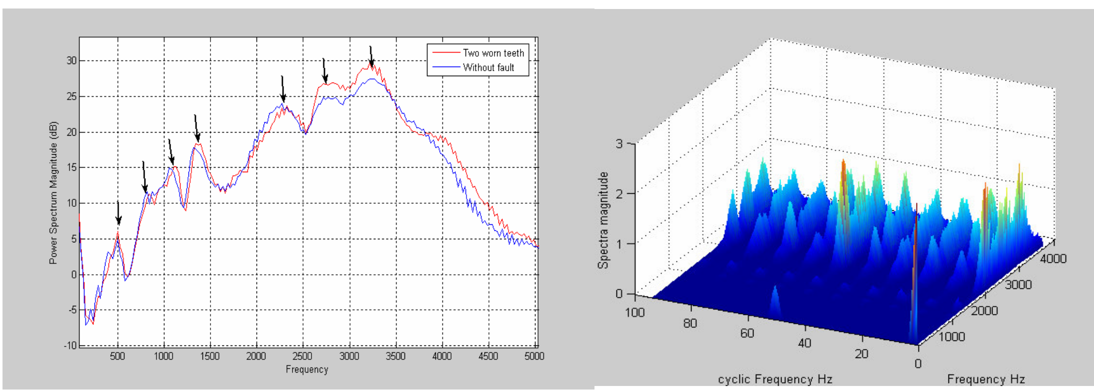


Figure 3. Typical milling signal

3.2. Analysis using second order statistics:

Figure (4-a) shows the power spectral density of the signal for the fault free case and for the two worn teeth. The arrows indicate the resonance frequencies. A first glance analysis of the spectrum shows that the resonance frequencies for the faulty case are slightly different from the fault free case. Table (2) presents these resonance frequencies and their ratios. It also shows that there is not a big difference in the magnitude of the two cases. As the condition of the cutting parameter is kept constant for all the experiments, it can be concluded that these variations are due to the change in the cutting tool state.



(a) (b)

Figure 4. (a) Spectral power density in two cases: without fault (blue) and two worn teeth (red). (b) Spectral correlation in the fault free case

Figure (4-b) shows the spectral correlation for the fault free case and is cyclic at multiples of $\alpha_0 = 10.833Hz$ (continuous spectra in the frequency axis and discrete in the α direction). The spectral correlation for the fault case is not presented here due to the limited space; however similar to the fault free case, no difference was noted in the magnitude of the spectra. At the cyclic frequency $\alpha = 5\alpha_0 = 54.146$ which coincides with the tooth frequency, the magnitude of spectrum is large compared to the other frequencies. This cyclic frequency will be use to compute the cyclic bispectrum.

The spectrum and spectral correlation are of second order statistics, and did not clearly distinguish between the different cases. So HOCS are attempted next to detect the quadratic phase coupling relation and cyclostationary links between the different harmonics, and to distinguish the good and faulty cases.

3.3. Analysis using higher order statistics:

Figure 5 (a, b, c and d) shows the cyclic bispectrum computed at the cyclic frequency $\alpha = 54.146Hz$ which corresponds to the tooth fundamental frequency ($5\alpha_0$). This cyclic frequency can be selected either by computing the cyclic bispectrum for all the cyclic frequencies and choosing the one which gives more information or by examining the spectrum of the signal, and selecting the harmonic which gives the best results. Generally we follow the last procedure because the first need more computations.

In the fault free case, figure (5-a), we have some peaks that correspond to the nonlinear and cyclostationary links between the different frequency components. These peaks characterize the vibratory signature in the fault free case. For the case of a worn tooth (figure 5-b) these peaks increase in magnitude and others appear. This results from the slight changes in the resonance frequencies, which affects the quadratic phase coupling and cyclostationnary links between periodical components.

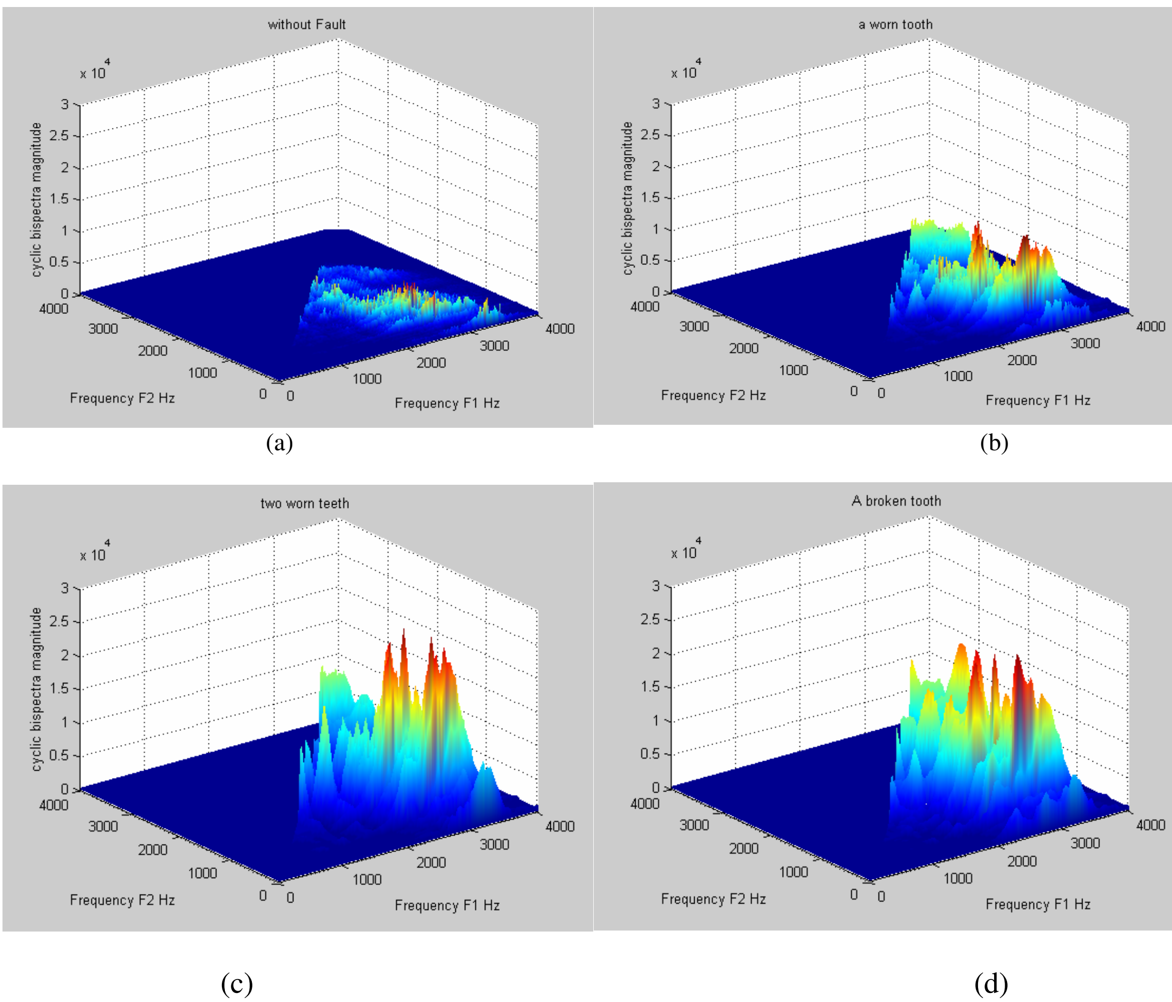


Figure 5. Cyclic bispectrum for $\alpha = 54Hz$ (a) without fault (b) a worn tooth (c) two worn teeth and (d) a broken tooth

In the case of the two worn teeth (figure 5-c), these peaks increase even more and is somehow similar to the case of the broken tooth (figure 5-d). As the severity of the defects increases, the cyclic bispectrum seems to be higher. This shows the aptitude of the cyclic bispectrum to detect wear in the advanced stages. A threshold can be established to alarm the operator. This threshold could be established with reference to the maximum peak in the fault free case (figure 5-a) and the faulty case for a worn tooth (figure 5-b).

4. CONCLUSION

In this paper, a diagnostic method of tool cutting based on the cyclostationary property and the higher order statistic has been presented. We benefited from the cyclostationary property of rotating machine to detect wear in the cutting tool. The HOCS which detect the bilinear and cyclostationary links allow the detection of faults in the cutting machine.

In the cutting tool monitoring, it is very important to detect the wear of the tool as early possible, because wear is the first stage towards tool breakage, and all current research aims on detecting it.

It is noted that these results are obtained only when the signal is taken under angular sampling. For lack of space the bispectrum classic of the temporal signal were not presented. The presented results in this case were limited. Our perspective in the next work is to establish a system based on the HOCS and synchronous average analysis to detects wear and to more specifically point out the worn tooth.

REFERENCES

[1] E.Dimla snr, “Sensor signals for tool-wear monitoring in metal cutting operations- a review of methods”, *inter. Journal of Machine Tools & Manufacture* **40** (2000)1073-1098.

[2] T. I. El-Wardany, D. GAO and M. A. Elbestawi, ”Tool condition monitoring in drilling using vibration signature analysis”, *inter. Journal of Machine Tools & Manufacture* **36**, No.6, pp,687-711, 1996.

[3] E. Dimla Snr, P.M. Lister, ”On-line metal cutting tool condition monitoring .II: tool-state classification using multi-layer perceptron neural networks”, *inter. Journal of Machine Tools & Manufacture* **40** (2000) 769-781.

[4] D.E. Dimla SR, P.M. Lister, “On-line metal cutting tool condition monitoring I: force and vibration analyses”, *inter. Journal of Machine Tools & Manufacture* **40** (2000)739-768

[5] Simonovski, M. Boltezar, J. Gradisek, E.Govekar, I. Grabec and A. Kuhelj, “Bispectral analysis of cutting process” *Mechanical Systems and Signal Processing* **16(6)**, 1093-1104, 2002.

[6] R.W. Barker, G-A. Klutke, M.J.Hinich, C.N Ramirez and R.J. Thornhill, “Development and Application of a Statistically based feature extraction algorithm for monitoring tool wear in circuit board assembly” *Journal of circuits, systems, and signal processing,* **vol.13**, Number 4,December, 1994.

[7] J.Antoni, F. Bonnardot, A. Raad, M. Elbadaoui,” Cyclostationnary modelling of rotating machine vibration signals” 2004 *Mechanical Systems and Signal Processing***18**(2004) 1285-1314,.

[8] L. Bouillau, M. Sidahmed, “Cyclostationary approach and bilinear approach: comparison, applications to early diagnosis for helicopter Gearbox and classification method based on HOCS”, *MSSP*,**15(5),**923-943 (2001).

[9] Chrysostomos L. Nikias, Mysore R. Rahuver, ”Bispectrum Estimation: A Digital Signal Processing Framework”, *IEEE* 1987, 0018-9219/87/0700-0869.

[10] Dandawate A.V., Giannakis G.B. “Nonparametric Polyspectral Estimators for kth-Order (Almost)Cyclostationary processes”, *IEEE Transactions on information theory*, **Vol.40**, NO.1, January 1994.

[11] William A. Gardner, Chad M. Spooner,”the cumulant theory of cyclostationary Time-series, Part I: Foundation” *IEEE Transactions on signal processing* **vol.42**. No.12,December 1994,

[12] William A. Gardner, Chad M. Spooner,” the cumulant theory of cyclostationary Time-series, Part II: Development and Applications”, *IEEE Transactions on signal processing* **vol.42**. No.12,December 1994,

[13] Amani Raad, ”Contributions aux statisitiques cycliques d’ordre supérieur: applications au diagnostic des défauts d’engrenage”, *thesis* Université de Technologie Compiègne. December 2003.