A shock filter for bearing slipping detection and multiple damage diagnosis

Bechir Badri [1]; Marc Thomas [1] and Sadok Sassi[2]

Abstract- This paper describes a filter that is designed to track shocks in the time domain, and to isolate them from any other random or harmonics components. This innovative tool can be used in the time domain as a denoising filter to estimate the proportion of the total signal energy caused by the shocks and to quantify the severity of damage. It can also be applied in the frequency domain and will allow through envelope or time-frequency analysis to clearly identify the sources of the shocks even if they are from various origins. This method makes also possible for differentiating the synchronous shocks from the pseudo-synchronous ones often caused by the slip of mechanisms and help to diagnose the severity of damage even with multiple defects.

***Keywords*—**Bearing, Shock Filter, Signal Processing, Vibration, Time-frequency analysis, Envelop, slipping, multiple defects.

I. INTRODUCTION

Machines maintenance is conditioned to an adequate monitoring of potential failures. Machinery vibration consists essentially of three signal types: Periodic (unbalance, misalignment, blade pass), random (friction, noise, fluctuation, turbulence) and shocks (bearing faults, gear faults, etc.). The determination of each of these types of vibration constitutes in itself a powerful monitoring technique. One of the most involved mechanisms in rotating machines failures are the bearings. The recognition and classification of bearings defects by vibratory analysis remains a subject of great interest in the rotating machines, because the detection of the damage phenomena and its propagation still remain nebulous to date. Precedent works allowed for the development of simulation software generating the vibratory response caused by defective bearings [1]. The numerical simulator has been used to generate a database covering a large range of defects configurations. A relevant review of vibration measurement methods for the detection of defects in rolling element bearings has been presented by Tandon and Choudhury [2]. The monitoring methods applied to bearings can be achieved in a number of ways [3]. Some of these methods are simple to use while others require sophisticated signal processing techniques. In fact, a large number of defects generate shocks that can be analyzed in either time domain: RMS, Peak, Crest Factor (CF), Kurtosis (Ku), Impulse Factor, Shape Factor, etc. [4], or in frequency domain: spectral analysis around bearing defect frequencies [5-7], frequency spectrum in the high frequency domain, Spike energy [8], enveloping [9], or time-frequency and wavelet analysis [10], etc.

The shocks are generally considered as abnormal phenomena in most rotating machinery and as reflecting the effect of defects for which the source must be identified. Usually shock phenomena can be identified by scalar time descriptors. RMS and Max-Peak values are quite adequate when the fault is quite developed and the signal-to-noise is high. Unfortunately, when the fault is small and the signal-to-noise ratio is weak, these two descriptors are not enough efficient alone. The increase in size defect is usually observed more readily by the Peak rather than by the RMS value. Because of this, the crest factor, which is defined by the ratio of the Peak to RMS value, is better adapted for monitoring the evolution of shock phenomena. This relationship between these two descriptors during the evolution of a fault is interesting, but it is easier to combine them in only one scalar descriptor such as the Crest Factor (CF) or the Kurtosis (Ku).

In this paper, a shock detector, based on the Julien Index [11-15] is described. The main goal of a Shock Filter (SF) is to examine the shock content into a signal. The method uses the time waveform and consists in recognizing the shock pattern of each defect, insulating it and treating it separately from the original signal. Thus, the effect of each defect in the vibratory signal is treated independently of the others and will make it possible to localize it and to distinguish the response from multiple defects. The shock descriptor also allows for counting the number of shocks per unit time, or better, for each cycle or revolution of the machine. This simple descriptor may be used by a non-specialist to monitor the number of shocks per revolution as the fault progresses. The shock detector allows not only for determining the number of shocks, but also their location and individual amplitudes. It is then possible to use the Fourier transform to determine the frequencies at which the shocks occur, similarly to an envelope analysis which would only react to shock signals, rather than to all the other manifestations of modulation phenomena. It is well known that bearings produce non-synchronous frequencies that can vary due to the slip phenomena that is not negligible. It is shown in this paper that applying a statistical method on the frequencies identified by the shock filter allows for identifying the slipping phenomena. Finally, the SF helps to diagnose the severity of each impact due to multiple defects, after introducing the information into a neural network.

Manuscript received July 24, 2011.

B. Badri and M. Thomas are from the department of Mechanical Engineering, ETS, Montreal, Qc, H3C 1K3, Canada, marc.thomas@etsmtl.ca

S. Sassi is from the department of Physics and Instrumentation, Institut National des Sciences Appliquées et de Technologie, Tunis, Cedex, Tunisia.

II. Procedure for Shock Filtering

With excellent properties to detect shocks and fast computing time, Kurtosis has been found the best time descriptor for evaluating energy level of the three windows [4].

$$Ku = \frac{\frac{1}{N}\sum_{k=1}^{N}(a_k - \bar{a})^4}{a_{RMS}^4} \tag{1}$$

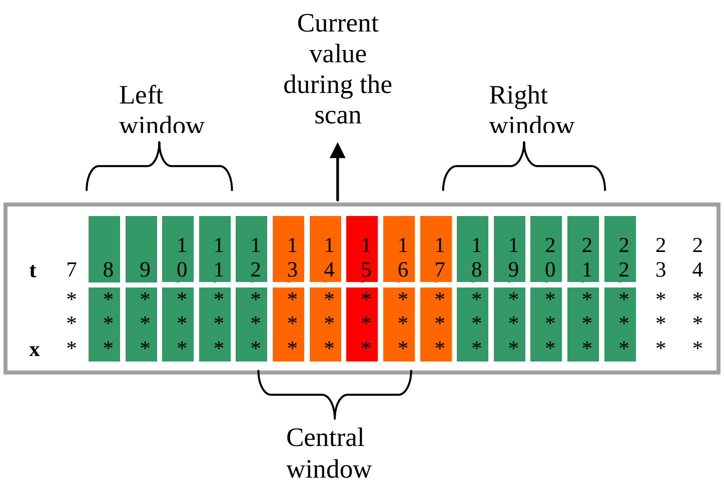
$$CF = \frac{a_{peak-\max}}{a_{RMS}} \tag{2}$$

with $a_{RMS} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} a_k^2}$ (3)

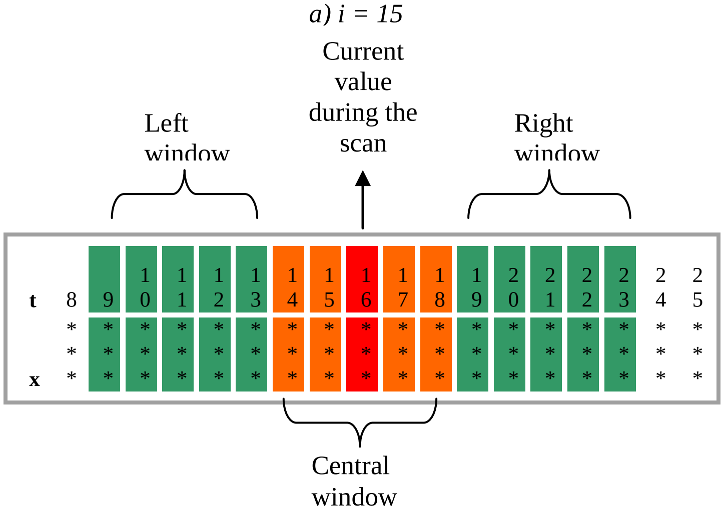
and $\bar{a} = \frac{1}{N}\sum_{k=1}^{N} a_k$ (4)

N being the number of samples in each window.

The Shock detector use three consecutive short-time filters sliding on the time signal (Fig. 1).



a) i = 15



b) i = 16

Fig. 1: Identification of short time windows

The Kurtosis into each window (central, left and right) is computed and compared to the two others. The procedure consists in scanning the sampled time block with a short window of 2n+1 samples. At each sample (i) of the time signal, the Kurtosis of a window C centered on i (i-n; i+n) is computed and compared to the ones calculated on windows located to the left L (i-3n; i-n) and right R (i+n; i+3n) of the current sample (i). Figure 1 shows an example for a time sample centered at i = 15, and a window length of 2*n+1 = 5; the central window is represented in orange and the windows to the right and left are in green.

Once the Kurtosis has been evaluated for each of the three windows, a classification and selection is conducted:

- If the energy of the central window is greater than the two others into the left and right window, we declare the presence of a shock and the peak amplitude of the signal at position (i) is assigned to the shock extractor.
- Otherwise, there is no shock and the shock extractor takes a nul value.

Then, the scan continues and the current position value is incremented to i+1 (figure 1-b). The procedure continues until the value i= N_{max}-(3n+1) is reached, where N_{max} is the total number of samples in our signal, and n is very close to the half-length of the short time window.

The size of the windows (R, L and C) highly depends on the acquisition parameters, mainly the sampling frequency, as well as the nature of the impact. Ideally, the window will be the same as the length of the transient response to an impact [16]. If we consider that the transient response is stabilized at, a level close to 4% of the maximum amplitude, the length of the windows may be defined as:

$$T = \frac{1}{2\zeta f_n} \tag{5}$$

with ζ, the damping rate and f_n, the dominant bearing resonance (Hz).

It is usual to consider a bearing damping rate of 5% and accordingly with the bearing size a dominant natural frequency between 3 and 5 kHz [9, 16]. We have tested the natural frequency of the bearing SKF 1210 at 4 kHz. This gives a T equal to 0.0025 s.

The length of the time window is:

$$T = 2n(\Delta t) = \frac{2n}{f_e} \tag{6}$$

where Δt is the time increment and f_e, the sampling frequency.

This gives a number of samples equal to:

$$2n = \frac{f_e}{2\zeta f_n} \tag{7}$$

By considering a sampling frequency of 48 000 Hz, we obtain 2n = 120 samples.

A Hamming window is applied to each shock with a width equal to the shock length plus twice the short window length defined by the shock filter. The different steps of the signal processing are described in Fig. 2.

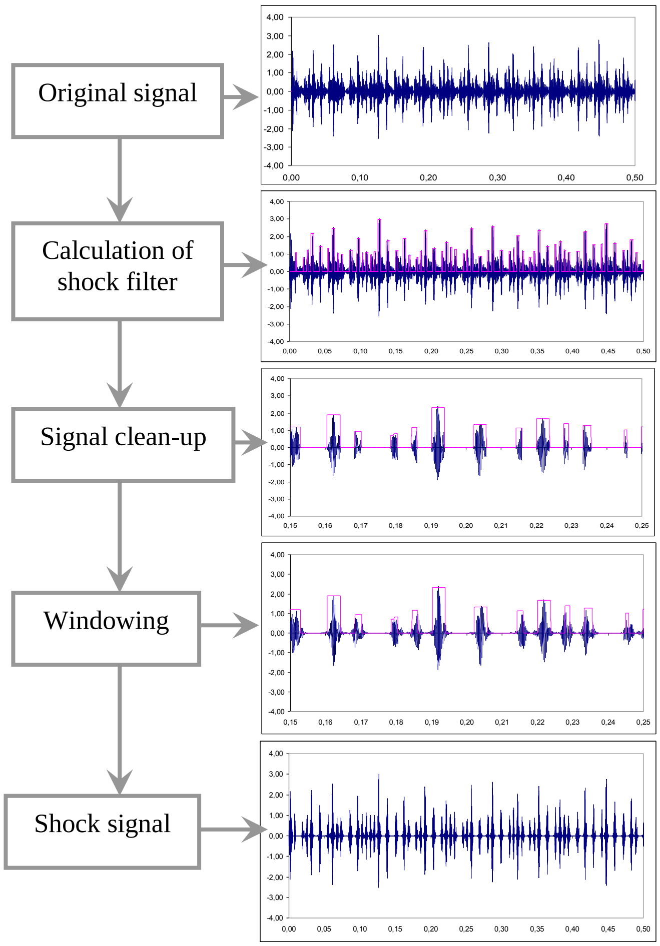


Fig. 2 Signal processing for shock filter

III. Time Analysis of the Shock Signal

The method previously described was applied on two signals recorded on two defective rolling-element bearings turning at a speed of 1750 RPM, one with an inner race spall of 0.18 mm and another of 0.56 mm. The results are shown on Fig. 3 and 4, respectively.

By computing the ratio of Crest Factor (CF) of the original signal on the CF of the Shock filter (SF), it is then possible to determine the proportion (CFR) of shocks (%) present in the original signal. Table 1 shows a summary of the results. This new descriptor (CFR) gives thus an indication on the severity of damage.

IV. The Time-Frequency Analysis of the Shock Signal

By applying a Short Time Frequency Transform (STFT) to the shock signal, it is then possible to determine the frequencies at which the shocks occur. This is particularly useful when the source of shocks must be identified since the STFT applied to the shock signal allows for determining which frequency range is excited by shocks.

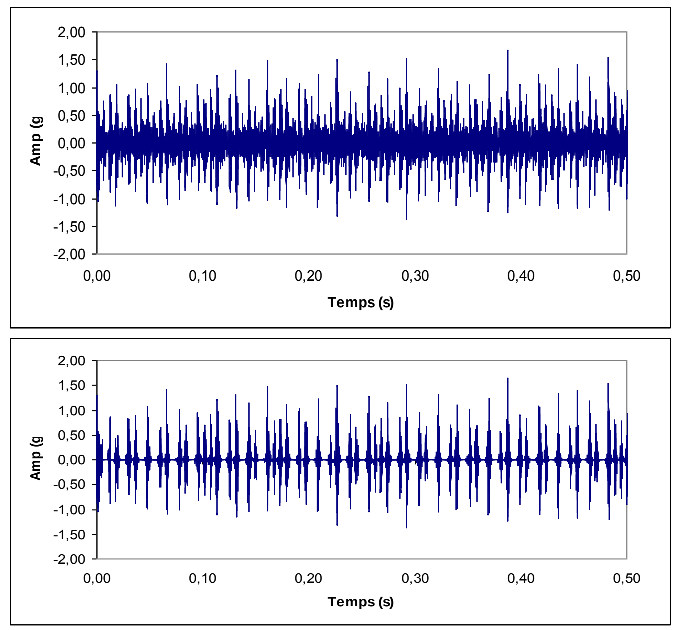


Fig. 3 Original and shock signals for a defect of 0.18 mm

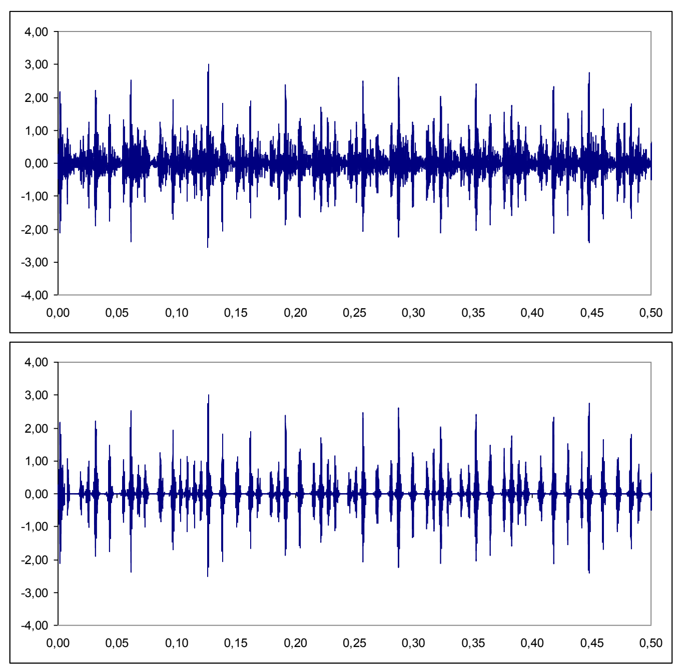


Fig. 4: Original and shock signal for a defect of 0.56 mm

Fig. 5 shows the Fourier transform of the signal processed on Fig. 4. The STFT analysis from the shock signal revealed to be clearer than those from the original signal (Fig.6).

Tab. 1 Computation of the shock/signal ratio

	Original (0.18 mm)	SF (0.18 mm)	Original (0.56 mm)	SF (0.56mm)
Peak	1.51	1.51	2.87	2.87
RMS	0.33	0.21	0.46	0.38
CF	4.57	7.19	6.24	7.56
CFR		**63.6 %**		**82.6 %**

As expected, the shock spectrum contains most of its energy in the high frequency range. The time-frequency analysis is thus very useful for identifying the natural frequencies excited by the transient shocks and the modulation frequencies cause by the defect.

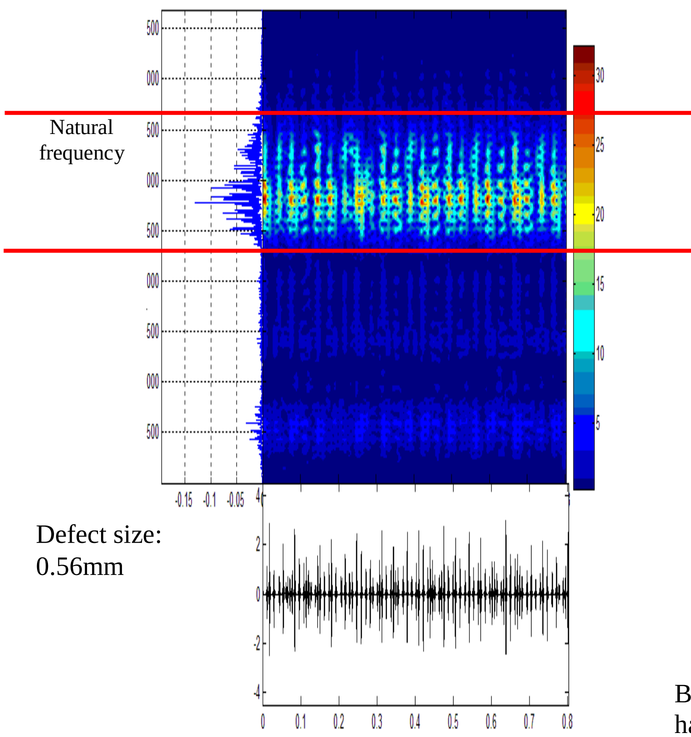


Fig. 5 Time-frequency analysis of the shock signal

V. The envelop analysis of the shock signal

The bearing frequencies that are excited by a defect are described accordingly with the bearing geometry [7]. At the second stage of degradation, these frequencies appear in modulation of the bearing natural frequency [6].

The Fundamental Train Frequency (FTF) reveals a problem on the bearing cage and appears usually in modulation of other bearing frequencies. It is close to 40% of the rotor angular speed. Eq. (8) is only true if the outer race is fixed.

$$FTF = \frac{\omega}{2}\left(1 - \frac{Bd(\cos\theta)}{Pd}\right) \tag{8}$$

where Bd is the ball diameter; Pd, the diametral pitch; θ, the contact angle; and ω, the rotor angular speed.

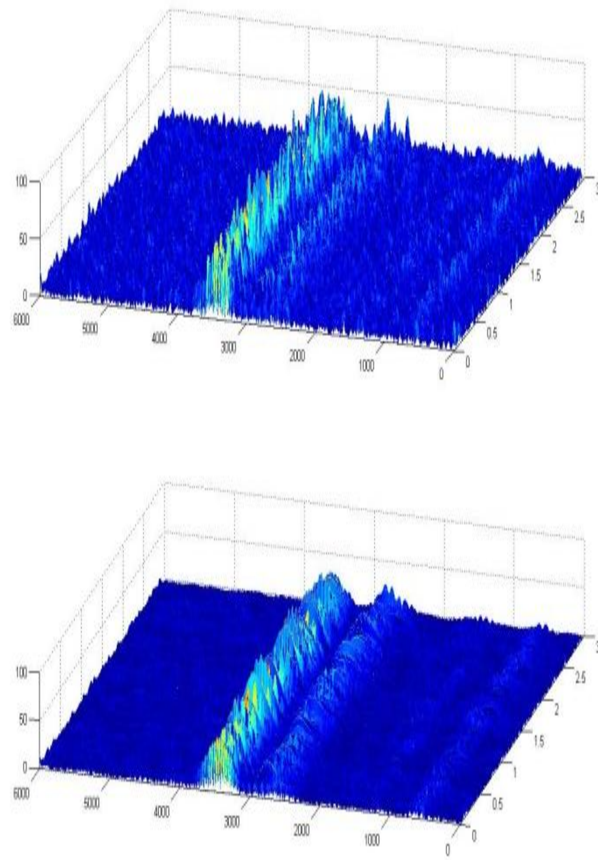


Fig. 6 Time-frequency analysis of a signal of a defective bearing (0.56mm) a) before and b) after applying SF

The Ball Pass Frequency on Outer race (BPFO) and the Ball Pass Frequency on Inner ace (BPFI) appears with their harmonics when a defect develops on outer or inner race respectively.

$$\begin{aligned} BPFO &= \frac{Nb}{2}\left(1 - \frac{Bd}{Pd}\cos\theta\right) \times \omega \\ BPFI &= \frac{Nb}{2}\left(1 + \frac{Bd}{Pd}\cos\theta\right) \times \omega \end{aligned} \tag{9}$$

The Ball Spin Frequency (BSF) reveals a defect on the balls. A defect on balls will excite 2BSF, since it strikes the inner race and the outer race in the same revolution.

$$BSF = \frac{Pd}{2Bd}\left[1 - \left(\frac{Bd}{Pd}\cos\theta\right)^2\right] \times \omega \tag{10}$$

These modulation frequencies can be easily identified from an envelope analysis or Hilbert transform [9]. The envelope analysis (also called amplitude demodulation) converts the modulation in amplitude or phase from a high frequency range to a low frequency range.

Fig. 7 shows an example of an envelope analysis performed on the shock signal of Fig.4 for a defect of 0.56 mm on the inner race.

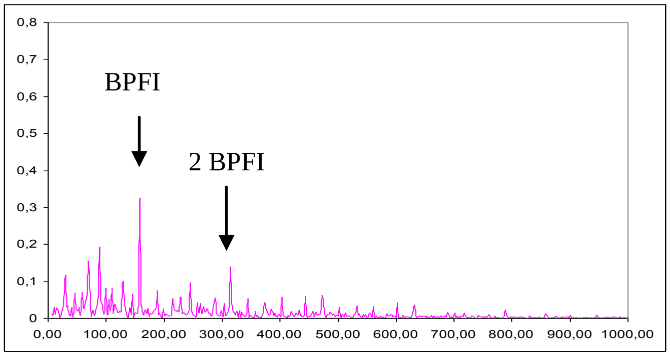


Fig. 7 Envelope spectrum of the shock signal

The presence of the Ball Pass Frequency Inner race (BPFI) and one of its 2nd harmonic in the shock spectrum indicate that the shocks are caused by a small defect on the inner race of the rolling-element bearing. The results obtained by this technique are less influenced by noise and interfering harmonics, which is very desirable when the signal-to-noise ratio is small.

VI. Detection of Bearing slipping

Indeed, in rotating machinery, one of the most complicated cases is observed when shocks are involving, in the same time, a damaged gear and bearing, and which appear in the same frequency band [17]. It is very important to note that defective gears will generate perfectly synchronous shocks, contrary to a bearing which even turning at constant speed will produce shocks which will be slightly asynchronous due to the slip phenomenon in the bearing. The shock filters allows for differentiating the perfectly synchronous shocks from the pseudo synchronous ones.

Two types of signals were generated: with and without slips.

- A basic signal which simulates a signal without slip, has been generated with a repetitive shock having a central frequency of 2500Hz with an amplitude of 7g and which is repeated at a frequency of 30 Hz. The time length is 4 seconds.
- A signal containing slip has been created by adding to the basic signal, a random frequency variation of 1 % to the repetition frequency. Thus the repetition frequency varies randomly between 29.7 and 30.3 Hz. This signal could simulate a bearing defect containing a slip.

A random signal of amplitude of 5g has been added to each one of these two signals. With a signal noise ratio of about 30%, the challenge consists in differentiating the two signals, even when they are drowned into the noise. The analysis of these two signals was initially done using the conventional signal processing methods.

Table 2 shows the usual scalar descriptor values for each signal. In spite of a small increase (6%) in certain scalar descriptors for signal with slip, the indicators do not allow us to conclude if or not the signal is slightly disturbed.

Time Indicators	*No slip*	*With slip*	*Relative difference (%)*
Kurtosis	10.4	10.62	2,07
Crest Factor	6.11	6.49	5,85
RMS	1.7	1.7	0
Peak	10.42	11.09	6,04
IF	9.56	10.21	6,36
SF	1.56	1.57	0,63

Tab. 2 Scalar descriptors

Even by analyzing each spectrum (Fig. 8) which indicates changes from which the cause is difficult to find, it is clear that it's very difficult, if not impossible, to distinguish the synchronous from the asynchronous shocks.

The method developed for classifying shocks and detecting slip, uses the normal law statistical method [11]. A random input x of mean value m and standard deviation σ follows a normal law N (m, σ^2). Its density function is :

$$f(x)=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(x-m)^2}{2\sigma^2}} \tag{11}$$

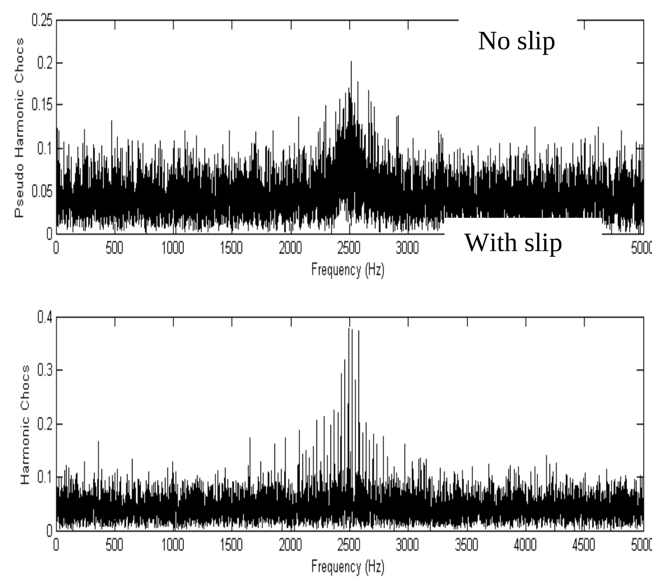


Fig. 8 Spectral analysis of signals with slip and no slip

By recording the period separating the shocks as determined by the shock filter, a population is defined after a sufficient lapse of a time. Having stored N periods separating the shocks, it is possible to trace the density of probability of period (or frequency) variation.

Figure 9 show the application of this new method for a signal slightly noised. The X-coordinate represents the period of shocks extracted from the filter and the Y-coordinate, the density of probability of period. The signal contains shocks at 30 Hz, thus corresponds to a period of 0,033s.

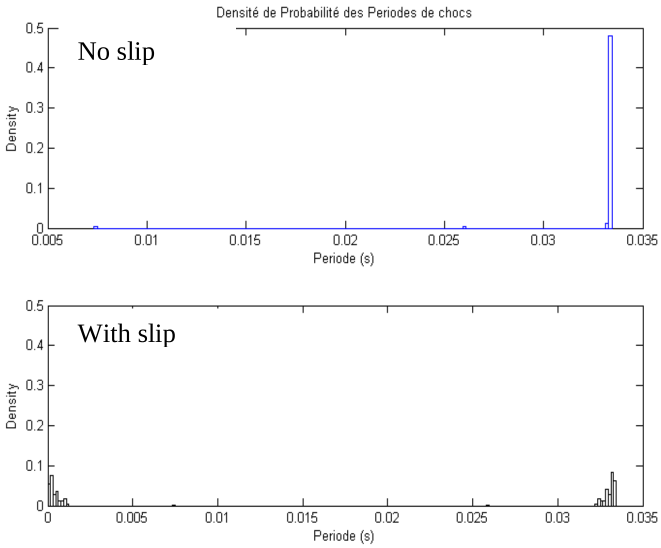


Fig. 9 Probability Density of shocks for a slightly noised signal

It can be noticed that a signal without slip reveals a high density of probability at its period and the probability to have a shock at the given frequency is 98.3%. On the other hand, a signal with slip presents a variation of its frequency and its the probability to have a shock at the given frequency is only 22.6%.

When the signal is strongly noised, a certain dispersion of the density of probability of period is revealed even for perfectly synchronous shocks (figure 10), because shocks are also detected at other periods, due to the added random component. This slightly disturbs the detection process of slip. However, it clearly appears that the density of probability is much higher for a signal containing synchronous shocks, even if the signal is strongly disturbed.

Consequently, we propose as a possible decision criterion able to be used as a follow-up parameter within the framework of a maintenance program, to monitor the probability to have a frequency of shocks. This parameter is extracted from the shock filter. It is important to note that the precision is highly correlated to the length of the recorded signal. Indeed, more shocks are in the signal, more the statistical population is large and thus, more the density of probability is precise. It is necessary to also note that the sampling frequency must be sufficiently large to detect the light drift in time, of the asynchronous pseudo shocks. If the shock derives with t_d, for optimal results, a 5 times smaller sampling period is recommended.

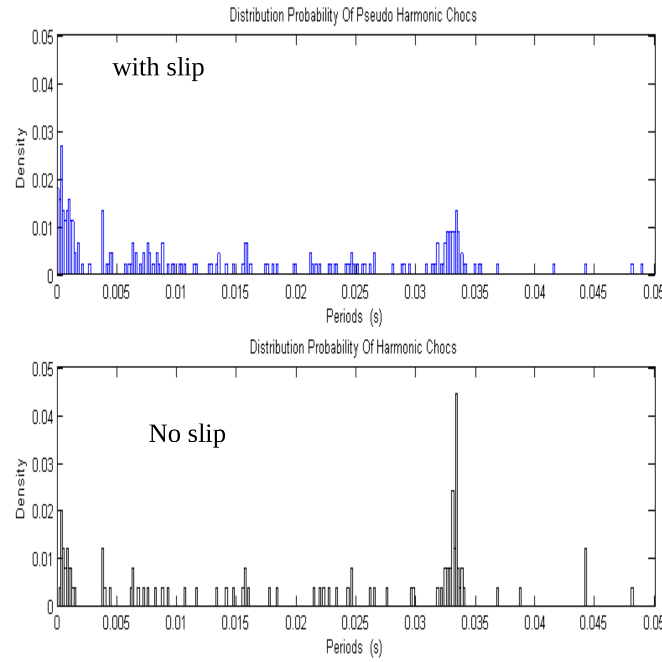


Fig.10 Probability density of shocks in a highly noised signal

Using this shock classification method, an application on experimental data coming from defective gears and bearings has been conducted.

The gears signals were taken from the test bench IDEFIX [18]. The test consisted in running the bench until complete destruction, with a daily measurement. The bench characteristics are described in table 3. The gear has one defective tooth and the signal has been token 2 days before the bench destruction. The shock filter has been applied on the time signal.

The other signal represents the application of the shock filter on a signal from a bearing with defect. The defective bearing signal comes from the CWRU data base [19]. The bearing is an SKF 6205 with a defect of 0.54mm on the external race, the speed was 1730 RPM. Its BPFO is 103 Hz (period = 0.0097 sec). The period of its second harmonic is 0.017 sec.

speed (tr/min)	1000 (period = 0.06 sec)	
Torque (daN.m)	200	
Gear mesh frequency (Hz)	333 (period 0.003 sec)	
Gears	1st Gear	2^{nd} Gear (tested one)
Teeth number	21	20

Tab. 3 Gear bench characteristics.

The density of probability of shocks periods for both signals is shown in Fig. 11. The analysis of bearing signal revealed the presence of peaks with a variable period T=1/BPFO for the bearing (103 Hz) and at the second harmonic of the shaft speed that is due to misalignment. For the gear, the frequencies detected are the rotor speed ($T=1/f_0$ for the gear (16.6Hz) : one shock per revolution) and with a small amplitude the gear mesh (T=1/20X 16.6). It's clearly demonstrated the dispersion induced by the slip at BPFO in the case of the bearing. This dispersion disappeared in the case of defective gears.

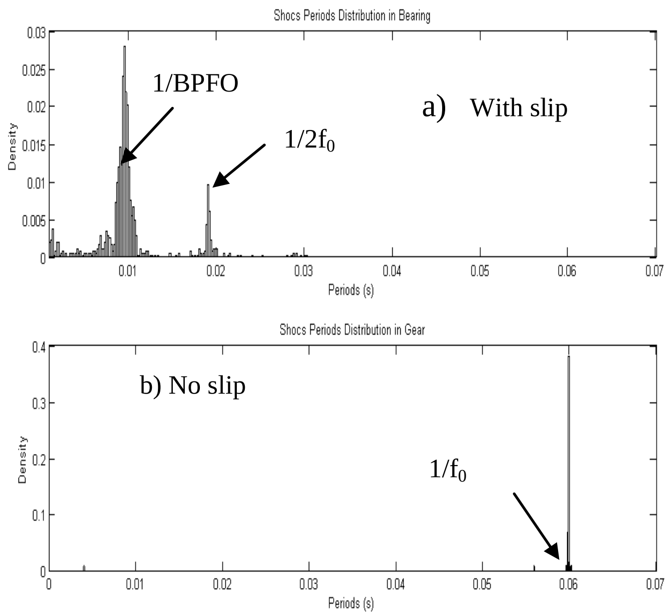


Fig. 11 Shocks probability density
a) bearing ; b) gears.

VII. DETECTION OF MULTIPLE DEFECTS

When a bearing exhibits multiple defects, it is very difficult to evaluate the severity of each localized defect. The Shock Filter (SF) will help to distinguish the signals coming from each defect and hence to diagnose the severity of each. Two defects have been simulated on the outer race of a SKF 1210 ETK9 bearing operating at 720 RPM: one of 1mm @ 0deg and the other of 0,8 mm @ 180deg. It can be noticed that introducing two defects at 180 degrees represents the most difficult case to identify. Thje forces produced bu each defects are shown in Fig. 12.

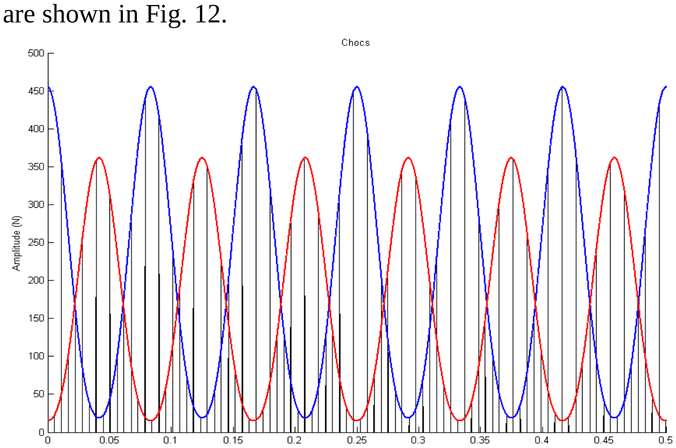
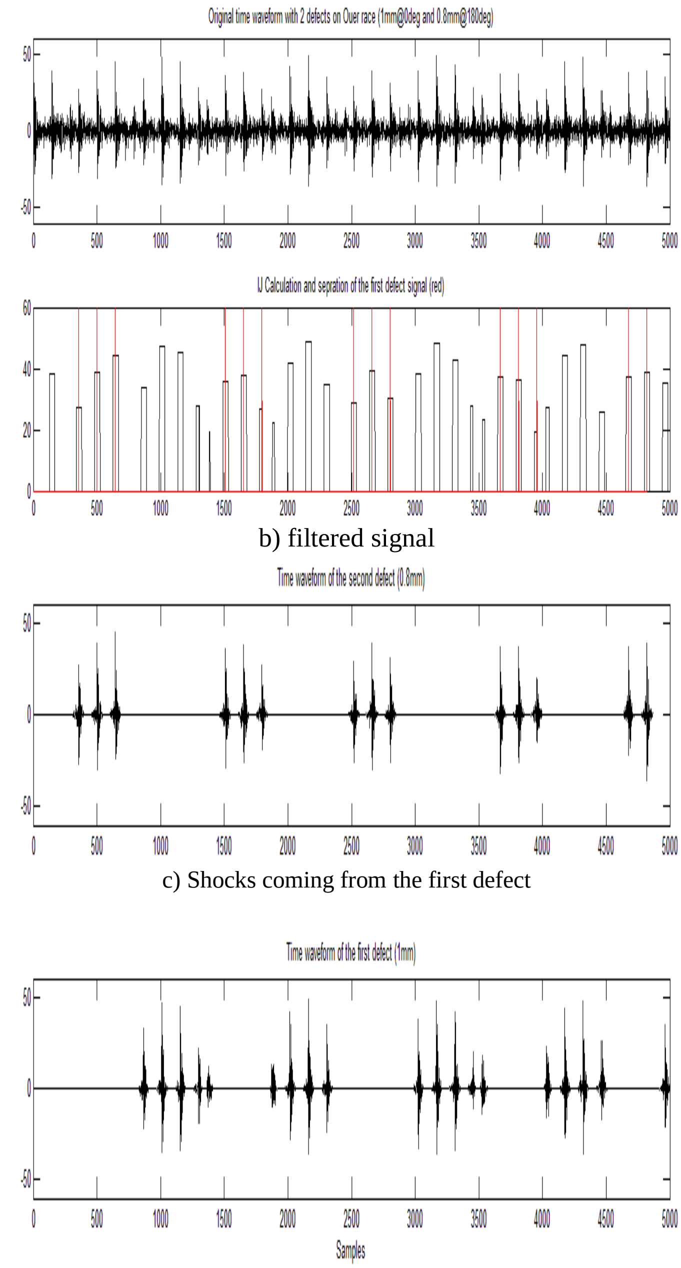


Fig. 12 Forces dues to defects at 180^o.

The acceleration response is shown in Fig.13-a and it can be noticed that it is very very difficult to diagnose a double impact from this figure.



b) filtered signal

c) Shocks coming from the first defect

d) Shocks coming from the 2nd defect

Fig. 13 Response due to two impacts.

a) Original signal, b) filtered signal, c) Response due to the first impact; d) response due to the 2nd impact.

Fig 13-b shows the filtered response with SF. It is easy from this figure to distinguish and to extract the shocks coming from each impact. Fig 13-c shows the filtered response dur to the first defect and Fig. 13-d shows the filtered response due to the 2nd defect.

All this information has been introduced in a neural network [20]. Two cases have been considered, one by analyzing the original signal (Fig. 13-a), and the other by analyzing the each filtered signal (Fig 13-c and 13d). The results are ahown in Fig. 14.

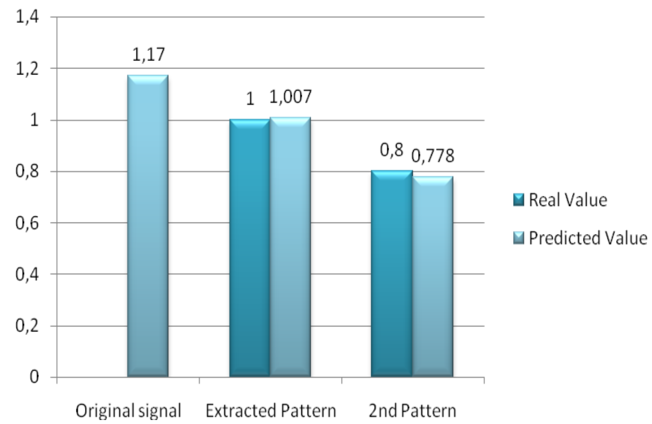


Fig 14. Severity of damage by neural network

In the first case, the diagnosis was over-estimated the size of the defect neither to distinguish each defect. In the second case, the severity of each defect was very well identified with a maximal error of 3%.

VIII. CONCLUSION

The present article describes the development of a signal processing technique in order to extract the shock content from a vibratory signal. It is called the Shock Filter (SF). This technique provides a cleaned up signal corresponding only to the contribution of the shocks, after having removed all the other components in the signal. A practical application is presented in order to illustrate its use and efficiency in diagnosis a defective rolling-element bearing. It is seen that this new tool provides an estimate of the severity of damage by comparing the shock signal from the original one. Furthermore the STFT of the shock signal reveal the natural frequencies of the system that are excited and an envelope analysis around the natural frequency range reveal the modulation frequencies that are characteristics of the source of damage. This method permits to distinguish between perfectly synchronous signals from signals with a small slip. The technique is very simple and powerful. It's build on basic statistic concepts, namely the density probability to have a shock period. This information is extracted from the shock filter. This new method has been applied with success to simulated signals and to experimental signals coming from gear and bearing signals and a comparative study of usual data processing methods showed that they were unable to distinguish a small slip. Consequently, we propose as a possible decision criterion able to be used as a follow-up parameter within the framework of a maintenance program, to monitor the probability to have a frequency of shocks, after filtering. The Shock Filter allows to identify the source of each impact in the case of multiple defects and the introduction of the filtered signals into a neural network allows for evaluating the severity of each defect.

ACKNOWLEDGMENT

The authors would like to thank the ONR for letting them use the signals from defective rolling-element bearings available on their site www.cwru.com , as well as the CRSNG for their financial help in this project.

REFERENCES

[1] Sassi S., Badri B. and Thomas M., 2007, A Numerical Model to Predict Damaged Bearing Vibrations *Journal of Vibration and Control*, Vol. 13, No. 11, Doi: 10.1177/1077546307080040, 1603-1628.
[2] Tandon N. and Choudhury A., 1999. *A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings*, Journal of Tribology International, 32, 469-480.
[3] Hammock C., 1996, *Evaluation of rolling element bearing condition*, Vibrations, Vol 12, No 3, pp 3 –8.
[4] Sassi S., Badri B. and Thomas M., 2008. Tracking surface degradation of ball bearings by means of new time domain scalar descriptors, *Proceedings of the International journal of Comadem*, 11 (3), 36-45.
[5] Schiltz R.L., 1990, *Forcing frequency Identification of rolling element bearings*, Sound and Vibration, Vol. 24, No 5, 4 p.
[6] Berry J., 1991, *How to track rolling bearing health with vibration signature analysis*, Sound and Vibration, pp. 24-35.
[7] Thomas M., Masounave J., Dao T.M., Le Dinh C.T. and Lafleur F, 1995. *Rolling element bearing degradation and vibration signature relationship*, 2nd international conference on monitoring and acoustical and vibratory diagnosis (SFM), Senlis, France, Vol.1, pp. 267-277.
[8] De Priego J.C.M., 2001. *The relationship between vibration spectra and spike energy spectra for an electric motor bearing defect*, Vibrations, Vol 17, No 1, pp 3 –5.
[9] Sheen Y.T., 2010, *An envelope analysis based on the resonance modes of the mechanical system for the bearing defect diagnosis.* Measurement 43 (2010) 912–934
[10] Hongbin M., 1995, *Application of wavelet analysis to detection of damages in rolling element bearings*, Proceedings of the international conference on structural dynamics, vibration, noise and control, pp 1334-1339.
[11] Badri B., Thomas M., Archambault R., Sassi S. and Lakis A., 2007, The Julien Transform to detect synchronous and asynchronous shock data, Proceedings of the 20th international conference of *Comadem07*, Faro, Portugal, pp 667- 676.
[12] Badri B., Thomas M., Archambault R., Sassi S., Lakis A. et Mureithi N., 2007, The Shock Extractor, *Proceedings of the 25th Seminar on machinery vibration*, *CMVA* 07, Saint John, NB, 11p.
[13] Thomas M., Archambault R. and Archambault J., 2004, A new technique to detect rolling element bearing faults: the Julien method, *Proceedings of the 5th international. Conference on acoustical and vibratory surveillance methods and diagnostic techniques*, Surveillance 5, Senlis, France, R61, 10 p.
[14] Thomas M., Archambault R. and Archambault J., 2003, Modified Julien Index as a shock detector: its application to detect rolling element bearing defect, *Proceedings of the 21th seminar on machinery vibration*, CMVA, Halifax (N.S.), 21.1-21.12.
[15] Archambault J., Archambault R. and Thomas M., 2002, A new Index for bearing fault detection, *Proceedings of the 20th seminar on machinery vibration*, Québec, 10 pages.
[16] Sawalhi N. and R.B. Randall, 2008. Simulating gear and bearing interactions in the presence of faults Part I. The combined gear bearing dynamic model and the simulation of localised bearing faults. *Mechanical Systems and Signal Processing* 22, 1952–1966.
[17] Antoni J. and Randall R.B. ,2002, "Differential diagnosis of gear and bearing faults", *ASME Journal of Vibration and acoustics*, Vol 124, pp 165-171.
[18] Bonnardot F., 2006, LASPI, U. St-Etienne, Banque de données, http://www.laspi.fr/vibrabase.
[19] Case Western Reserve University, 2006. bearing data center. http://www.eecs.cwru.edu/laboratory /bearing/download.htm.
[20] Badri B., Thomas M. , Sassi S. and Lakis A., 2007, Combination of bearing defect simulator and artificial neural network for the diagnosis of damaged bearings, *Proceedings of the 20th international conference of Comadem07*, Faro, Portugal, pp 175- 185.

BIOGRAPHIES

Bechir Badri (M. Ing), is finishing his Ph.D in mechanical engineering at the ETS (Montreal). He also has M.Ing, graduated in Mechanical Engineering from ÉTS. Working for more than 10 years in the field of vibration and structural dynamics, he specializes in the study of bearings vibration and machines monitoring, but especially in the development of new tools and methods of signal processing. With this experience, he founded Betavib company, a company developing a new generation of collectors / analyzers.

Marc Thomas is professor in mechanical engineering at the ÉTS (Montreal) since 18 years. He has a Ph.D. in mechanical engineering from Sherbrooke university. His research interests are in vibration analysis and predictive maintenance. He is the leader of a research group in structural dynamics (Dynamo) and an active member of the Canadian machinery Vibration Association (CMVA). He is the author of two books: 'Reliability and predictive maintenance of machines' and 'Simulations of mechanical vibrations with Matlab and Ansys'. He has acquired a large industrial experience as the group leader at the Quebec Industrial Research Center (CRIQ) for 11 years.

Sadok Sassi is an expert in vibration analysis and troubleshooting of mechanical installations and equipments. He is currently conducting research on different areas of mechanical engineering and industrial maintenance. His most significant contributions are the development of powerful software called 'BEAT' for vibration simulation of damaged bearings and the design of an innovative intelligent damper based on electro and magneto rheological fluids for the optimum control of car suspensions.