BEARING DEFECTS SIGNALS DEMODULATION USING SHOCK FILTERS

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<u>Abstract:</u> A fundamental problem in the development of faults detection and diagnoses methods is to obtain fault signature data as clear as is possible. This article is focused on vibration signals generated by rolling bearings with localized defects
A demodulation method is presented for rolling bearings defects signals, which is used on detection of defects signatures (frequencies). The proposed demodulation methods are based on one dimensional shock filters, which are intensively used on image processing but as two dimensional filters. Different shock filters implementations used for the demodulation method are provided together with a comparison of the results. In order to get a clearer result of the frequency localization for the rolling bearing defects, the shock filter formalism is used together with a Gaussian filtering technique. Then, based on these approaches and on a demodulation method, an identification of the defects is obtained. The obtained results are then compared with a demodulation method which is based on the complex shock filters. The experimental results are in favor of complex shock filter approach, which we considered to be a better approach successfully applied in identification of rolling bearing defects.

Keywords: *shock filter, bearing defect, demodulation, envelope detection, vibration*

I. INTRODUCTION

The mathematical approach that uses the equations with partial derivatives is a relative old concept which, on the other side, has many new applications. PDE (Partial Differential Equation) can be used to describe a wide area of physical phenomena such as vibration, sound, electrodynamics, fluid flow, or elasticity. One interesting area where the PDE can give important results is the signal processing field. This study is focused on the vibration signals determined by the roller bearing movements. In mechanical systems, bearings are parts considered the most exposed and are consequently more subject to degradation. These roller bearings are very important components in many economic fields including here transportation, industry, agriculture etc, but, at some point in their duration of use, they might have some defects.

Defects could appear on different parts of bearings and generate shock pulses at the contact of defect with bearing parts. There are several studies in regards with the topic of roller bearing signal analysis, which treat this problem by using different approaches.

Giovanni Rinaldi [7] applies a band-pass filter to extract the bearing defects signature by analyzing the defect frequencies that are visible using FFT (Fast Fourier Transform). Using different demodulation techniques, the noise and natural frequencies are significant reduced.

In this paper we study the vibration signals generated by bearings affected by localized defects. The obtained signals are demodulated using shock filters in order to enhance the defects signatures detection. The approach presented in this study is using the shock filtering as a tool for envelope detection which provides a demodulation of the vibration signal by removing all unneeded high frequencies and some noise components, so that there are enhanced the amplitude related to defects frequencies.

Shock filters are intensively used on image processing as 2D filter of image matrix. In 1D filtering area shock filters were not used at maximum potential, and bearing defect signals is one of the 1D signal which could be very well demodulate (denoising) using shock filters.

The proposed approach used for the enhancement of defect detection procedure is presented with more details in following section of this study. Thus, the rest of the paper is organized as follows: the second section present the principal theoretical aspects related to the shock filters. There is made a briefly review of the most used shock filters formalisms. Then in the third section we presented the used signals, which are generated by roller bearings movements having localized defects. This section includes also a description in regards to frequency of these defects. In the fourth and fifth section of the paper we describe the used methodology and we present the (experimental) results.

II. THE SHOCK FILTER FORMALISM AND LITERATURE REVIEW

The proposed approach which is used for roller bearing defect detection is known in the literature as the shock filter formalism. The shock filter was introduced by Osher and Rudin [2] in 1990 as dedicated domain inside the main filed of PDEs. It is considered that the shock filters are approximating well the deconvolution of the analyzed signal with the filter series coefficients and these filters can be successfully used as a very good deblurring method. Thus, the shock filters are based on the principle that the zero crossing points of the signal Laplacian are the edge detectors [4].

Therefore, the shock filter equation is:

$$I_t = \frac{\partial I}{\partial t} = -F(I_{dd})|I_d| \qquad (1)$$

where *I* represents the signal which is filtered and I_d and I_{dd} represent the first, respectively the second directional derivatives of the signal *I*. The notation for the signal is *I* since it is used for both image and signals.

The function F should satisfy the next condition, as stated also in [2]:

$$F(0) = 0,\ F(s)sign(s) \geq 0 \qquad (2)$$

Then , a classical scheme for the shock filter is considered to be like :

$$I_t = \frac{\partial I}{\partial t} = -sign(I_{dd})|I_d| \qquad (3)$$

The shock filter equation (1) could be approximated by the following discrete representation, which is presented in the research of Gilboa [1]:

$$I_i^{n+1} = I_i^n - \Delta t|DI_i^n|sign(D^2 I_i^n) \qquad (4)$$

where

$$DI_i^n = m(\Delta_+ I_i^n, \Delta_- I_i^n)/h \qquad (5)$$

and

$$D^2 I_i^n = (\Delta_+ \Delta_- I_i^n)/h^2 \qquad (6)$$

In the equation (5), $m(x, y)$ is the minmod function [2]:

$$m(x,y) = \begin{cases} sign(x)\min(|x|,|y|) & \text{if } xy > 0, \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

and $\Delta_\pm = \pm(u_{i\pm1} - u_i)$. The CFL (Courant–Friedrichs–Lewy) condition in the 1D case is $\Delta t \leq 0.5h$.

There are some important features of shock filter which are frequently used in image and signal processing [1]. Some of the most important characteristics are mentioned in this paragraph. Thus, shocks are generated at inflection points (i.e. – the roots of second derivatives). The local extreme values are not changed by filtering and also there are no created other local extremes. This property is known as "total variation preserving" (TVP) of the filter.

When using the shock filters in image processing, it is important to get a good filtering of the noise which overlaps the image. When using a shock filters in image denoising, the image will become more blurry than it was the initial one, that is, this process is very sensitive to noise. The theoretical fact, on which this statement is based, relays on the idea that the noise added to signal will add also many inflexion point so that the filtering process is affected completely. Sometimes the discretization could be a solution for reducing this effect, but the sensitivity to noise will still persist. Hence, a signal affected by noise will not be enhanced by a shock filter processing since the process could lead to the side effect of noise amplification. There are also other facts on which the discrete representations of shock filter are based. A more detailed description about discretization aspects of the shock filter and their features could be found in [1].

An improvement of the Osher-Rudin model was made by Alvarez and Mazora [3] who are proposing a more robust filter by convolving the I_{dd} with a low pass Gaussian filter.

$$I_t = \frac{\partial I}{\partial t} = -sign(G_\sigma * I_{dd})|I_d| \qquad (8)$$

where G_σ is the Gaussian kernel of standard deviation σ:

$$G_\sigma(x) = \frac{e^{-x^2/2\sigma^2}}{\sigma\sqrt{2\pi}} \qquad (9)$$

The shock filter proposed by Alvarez and Mazora is unfortunately not useful in 1D signal processing because of the lost of diffusion part, but we consider it very important since it uses as preprocessing method the Gaussian filtering. Furthermore, other researchers considered that putting together the shock part and the diffusion can bring a filter improvement [1].

The previous expression and equations are used in case of continuous signals. The discrete representation which is use in practice will lead to some truncating of the integrals and the convolution is implemented as a finite sum as it follows [5]:

$$F[x] = \sum_{k=-K}^{K} f[x-k]g[k], \text{ for any } x. \qquad (10)$$

In the previous equation $F[k]$ is the discrete version of the filtered continuous signal $f(x)$ and $g[k]$ is the discrete version of the Gaussian signal g(x) when a sampling is realized for the integers indexes $k \in \mathbb{Z}$. In a continuous framework $g(x)$ will reach zero as $x \to \pm\infty$. In the discrete domain the interval definition could be resized to a finite one since this function converged towards zero with an exponential speed. This means that if k is chosen to be equal to the largest integer value close to 3σ or 5σ, then there is no significantly loss of precision due to discretization and truncation of continuous signal. The result of this filtering $F[k]$ is the Gaussian finite impulse response (GFIR) [5].

An important improvement of shock filters was made by recently by some researches, including here the name of Gilboa [1]. They "added another dimension" to the existing equations of shock filters by introducing the complex shock filter:

$$I_t = -\frac{2}{\pi} artan(a\mathrm{Im}(\frac{I}{\theta}))|I_d| + \lambda I_{dd} \qquad (11)$$

where $\lambda = re^{i\theta}$ is a complex scalar.

One of the advantages of complex shock filter is that the convolving of signal for each iteration is not needed anymore. The imaginary part of the equation (11) provides a good feedback and could be a good controlling method of the process, better than a second derivative [1]. Another advantage of the complex shock filters is referring to the good results which can be obtained for one dimensional signal processing. The process of applying the complex filtering is by its definition time dependent, so there is no needed a special time framework approach. Thus, a complex filter works as a combination between shock filter and linear diffusion [1].

The equation (11) is the central element which we has been used also in our implementation. Since this equation is represented in continuous time frame, then it discrete approximation is represented as it follows:

$$I_i^{n+1} = I_i^n - \Delta t \frac{2}{\pi} \arctan(\frac{a}{\theta}\mathrm{Im}(I_i^n))|DI_i^n| + \lambda(D^2 I_i^n) \qquad (12)$$

the CFL condition is $\Delta t \le 0.5h^2 \frac{\cos\theta}{r}$.

III. BEARING DEFECTS SIGNAL

On this paper we are studying bearing defects which could be localized on inner race, outer race or balls.

Culita, Stefanoiu and Ionescu [5] presented a simulation vibration model, a basic model of vibration generated by single point defects in bearings. They present how the defect is encoded by vibration in a more accurate and natural manner than previous models.

When a rolling ball cross thru a defect, the impact power suffered by bearing ball system depends of all contact parts relative speeds and external applied strained. Therefore, defects appeared on different parts of bearings, generate shock pulses with some specific and known frequencies.

Assuming a general configuration where both rings may rotate, f_r is the frequency of relative rotation between races.

The different frequencies generated by a bearing and which help us to identify the defects, and more important to localize the defects are presented as follow (by assuming the ball does not slide on the races):

$$f_{out} = \frac{n_b f_r}{2}\left[1 - \frac{D_b}{D_p}\cos\alpha\right] \qquad (13.1)$$

$$f_{in} = \frac{n_b f_r}{2}\left[1 + \frac{D_b}{D_p}\cos\alpha\right] \qquad (13.2)$$

$$f_{cout} = \frac{f_{out}}{n_b}\ ,\ f_{cin} = \frac{f_{oin}}{n_b} \qquad (13.3)$$

$$f_b = \frac{f_r}{2}\left[1 - \left(\frac{D_b}{D_p}\cos\alpha\right)^2\right] \qquad (13.4)$$

f_{out} - the ball pass frequency on the outer race

f_{in} - the ball pass frequency on the inner race

f_{cout} - the cage rotation frequency with respect to the outer race

f_{cin} - the cage rotation frequency with respect to the inner race

f_b - the ball rotation frequency (spin rotation)

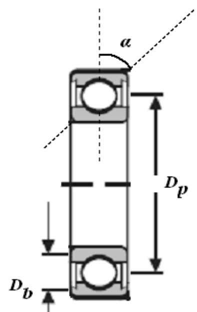

Figure 1. Bearing parameters

Where n_b is the number of rolling elements, D_b and D_p are the ball diameter and respectively the average (pitch) diameter and α is the contact angle (loading angle). The bearing parameters are illustrated on the Figure 1.

IV. METHODOLOGY AND USED DATA

The approach used on this study is based on the theoretical elements presented in the previous section. Before directly applying the complex shock filters on the analyzed signals, we did some investigations in regards with other shock filtering techniques.

The analyses signals are obtained using accelerometers which capture the vibrations generated by bearings with localized defects. The experimental data used for analysis were obtained from the "Bearing Data Center (B.D.C.)" Website of CaseWestern Reserve University, Cleveland, Ohio, USA (2006) [8].

We decide to use on this paper for demutualization a signal obtained from a bearing with defect localized on inner race because in this case the rotation frequency is modulated by the ball pass frequency on the inner race (f_{in}) of shock pulses, and the pulses are modulated by natural frequency which is the highest frequency.

The main goal is to eliminate using demodulation methods the highest frequency and obtain the pulses as simple and clear as possible. A second goal is to obtain the rotation frequency also pretty clear in order to be easier detected because this frequency say what kind of defect we have an inner race or an outer race defect.

Experimental data were collected with a rate of 12 000 samples per second. The next figure presents the experimental data obtained from a SKF 6205 bearing with a defect of 0.021" located on inner race.

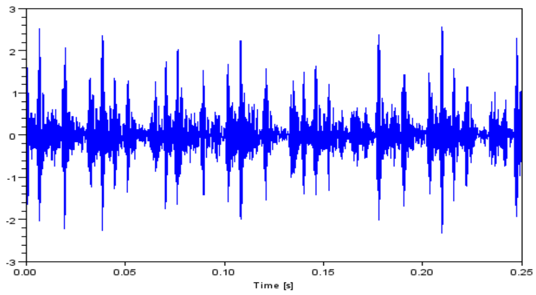

Figure 2. Vibration data for bearing with a defect of 0.021" located on inner race

These data will be used to prove the results of different filtering methods on the next sections.

V. RESULTS

Based on the theoretical presentation of shock filters we used different shock filters methods in order to find the best approach for bearing defects signals demodulation.

The first step was to apply a classical shock filter to studied data. The results were not useful because of the property of shock filter to enhance the noise.

We can observe on Figure 3 that the difference between modulus of signal (green color) and filtered signal (red color) is not significant.

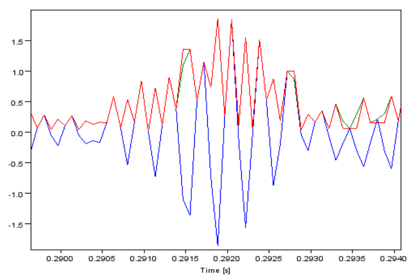

Figure 3. Classical shock filtering of absolut value of signal

On the next step we used the Alvarez and Mazora shock filter, but the results were not significant different than the classical shock filter. It is known that the Alvarez and Mazora have not relevant better results for 1D filtering. The Figure 4 shows all of these – green color is the modulus of signal and red color is represented the filtered signal.

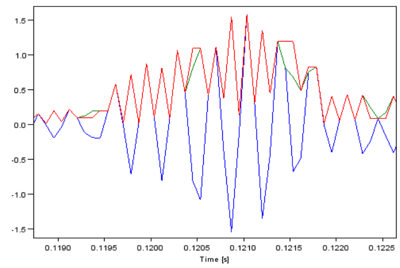

Figure 4. Alvarez and Mazora shock filtering of absolut value of signal

Accordingly with the approach used in the work of Alvarez and Mazora concerning the shock filters, we used as envelope detection method the Gaussian filtering alone. We did the implementation for $\sigma = 28$.

The obtained results are good from the point of view of signal demodulation. The Figure 5 and Figure 6 present the results obtained applying the Gaussian filter. The first picture presents an overview of the Gaussian filtering and on the second picture we can see a more detailed presentation. The filtered signal is represented using red color and the modulus of signal using green.

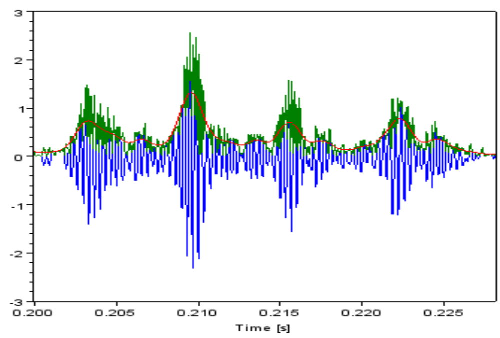

Figure 5. Gaussian filtering of absolut value of signal

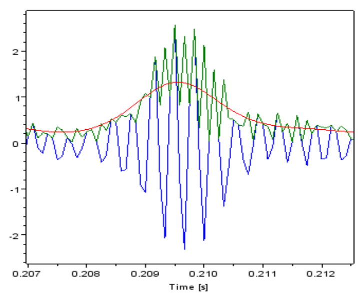

Figure 6. Detailed view of Gaussian filtering of absolut value of signal

The complex shock filter could also be used for bearing defects signal demodulation. We analyzed the behavior of complex shock filter in two different configurations presented in the Table 1.

Configuration name	$\|\lambda\|$	a	iteration
Complex Shock 1	0.1	0.3	100
Complex Shock 2	0.3	0.6	200

Table 1. Complex Shock filtering configurations

The Figure 7 and Figure 8 present the results obtained using complex Shock filtering in two different configurations and the comparison with the Gaussian filtering.

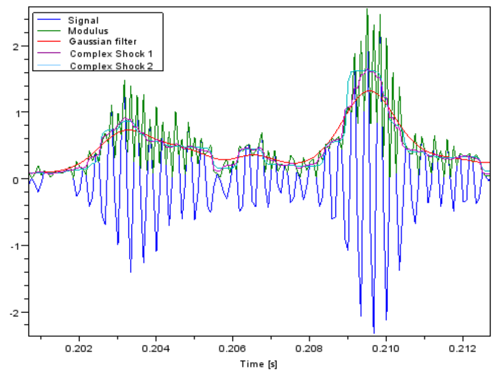

Figure 7. Complex Shock filtering of absolut value of signal

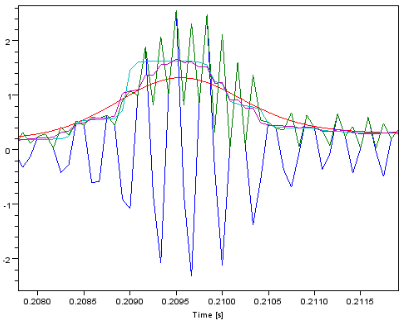

Figure 8. Detailed view of Complex Shock filtering of absolut value of signal

The results looks to be better than using previous presented shock filters or Gaussian filtering demodulation method. Complex Shock filtering looks like the best envelop detection, comparing with the classical shock filtering and the Gaussian one.

In order to have a better view of different methods of bearing defects signal demodulation a frequency Fourier spectrum is presented on Figure 8 as follow: the picture from top-left corner represent the frequency spectrum of unfiltered experimental signal, the top-right picture represent the frequency spectrum of Gaussian filtered signal and the bottom picture represent two frequency spectrums of Complex Shock filtered signal using two different configuration presented above (Complex Shock 1 on the left and Complex shock 2 on the right).

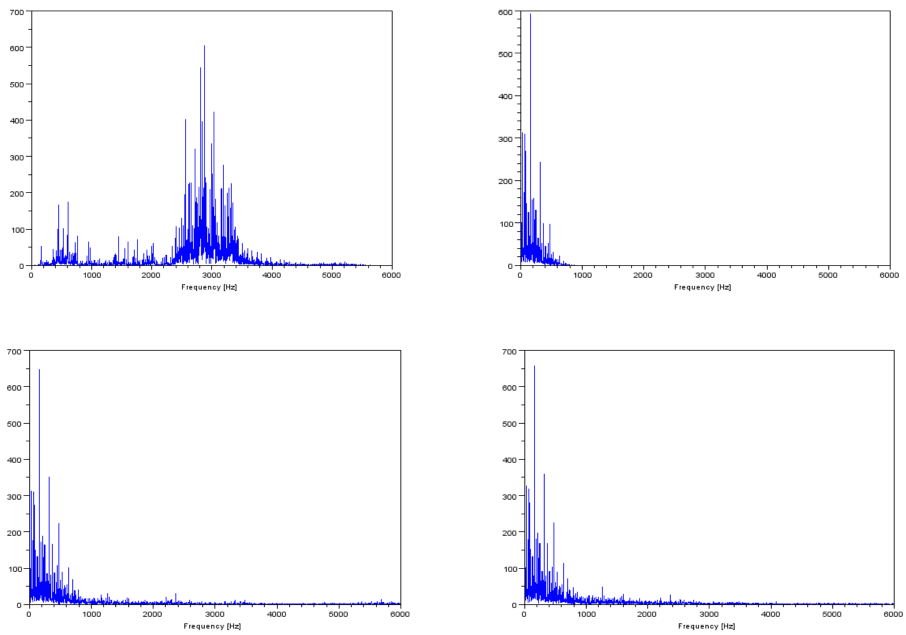

Figure 8. Frequencies spectrum of unfiltered experimental signal, gaussian and complex filtered signal

A better view with a focus on low frequencies of spectrum is provided by Figure 9 which presents the comparison between frequency spectrum of demodulated signals obtained by Gaussian filtering and complex shock filtering (Complex Shock 1 configuration). Also the defect frequencies are shown: the ball pass frequency on the inner race (f_{in}) is the most important, and also the rotation frequency (f_r) is easy visible. Because the f_{in} is amplitude modulated by f_r we can observe on the frequency spectrum the frequencies $f_{in} - f_r$ and $f_{in} + f_r$. Using these frequencies well visible on the frequency spectrum we can consider the inner race defect detected.

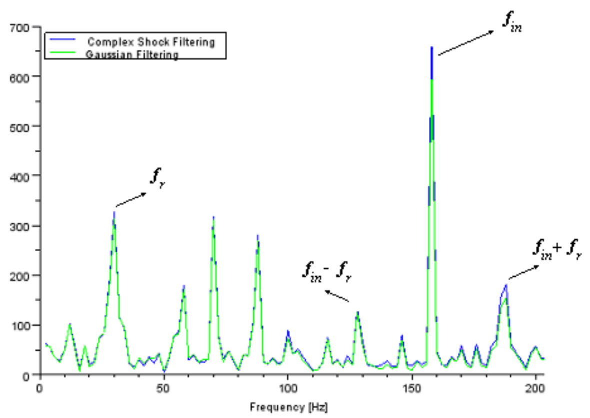

Figure 9. Frequencies spectrum of gaussian and complex filtered signal

An important advantage of Gaussian filtering is the denoising ability comparing with shock filters.

Also complex shock filters have a better denoising ability than any other shock filter, and also have a better envelope detection property than Gaussian filter, and then could be the best presented solution for bearing defects signals demodulation. On Figure 8 we can observe that the magnitude of f_{in} obtained using complex shock filtering is 647.90443 comparing with the magnitude of f_{in} obtained using Gaussian filtering which is 594.47709.

VI. CONCLUSIONS

In this study we showed that the approach of using complex filter could improve the performances in bearing defect frequency detection. We showed that a simple Fourier Transform will lead to a noisy representation from which the defect could not be very easy identified. Thus, some filtering techniques are needed. The shock filter approach which is used with success in domain like image edge detection has been applied also in the field of rolling bearing defect detection. The approach which makes use of classical shock filter give also good results but the improvement bring by complex shock filter is obviously.

The current research is an attempt for improving methods used for detection of roller bearing defect. The implemented method based on the approach which eliminates the highest frequency and which obtains the defects frequencies using demodulation involving shock filters, has lead to important results. Based on the obtained results a better performance of roller bearing defect frequency detection has been achieved.

As future research it is possible that the usage of imaginary part of complex shock filter might lead to some additional improvements. The imaginary part is also used for a better controlling of the shock detection and a proper calibration of the used parameters can also have benefic effect.

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