Proceedings of the 25th Seminar on machinery vibration, *CMVA* , October 2007, Saint John, NB

THE SHOCK EXTRACTOR

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ABSTRACT

Previous works made possible to partially achieve the detection and the severity of degradation for a defective bearing, using an appropriate neural network, but only for a restricted number of localized defects. To avoid this limitation, a new technique has been developed for a better characterization and recognition without restriction of bearings defects number. This technique, called *the shocks extractor*, consists in associating the neural network to an advanced technique of signal processing. The method, using the time waveform, consists to recognize, the pattern of each defect, to extract and treat it separately of the original signal. Thus, the effect of each defect in the vibratory signal can be treated independently of the others that make possible to localize the default and to recognize its severity of degradation.

KEYWORDS: vibration, shock detection, synchronous signal, bearing, pattern recognition

1. INTRODUCTION

The Julien Index (JI) was initially developed in the time domain, in order to identify the presence of shocks in a time signal (Archambault et al, 2002; Thomas et al, 2003). Simplicity and convenience are perhaps the main advantages of this indicator. The Julien Index is directly connected to shocks, which are generally considered as abnormal phenomena in most rotating machinery, in contrast to other indicators which are derived from mathematical formulae and are therefore sometimes disconnected from the underlying physical phenomena as seek by the practitioner. Sometimes later, the Julien Transform (JT) was developed in the frequency domain (Thomas et al 2004, Badri et al 2005). It was mainly designed, not only for identifying the number of shocks and their amplitude, but also their location. In fact, 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.

Indeed, in rotating machinery, one of the most complicated cases is observed when shocks are simultaneously involving damaged gears and damaged bearings that may appear in the same frequency band (Antoni and Randall, 2002). It is very important to note that a defective gear will generate perfectly synchronous shocks, contrary to a damaged bearing which even turning at constant speed, and due to the slip phenomenon between its moving parts, may produce asynchronous shocks. This work treats the use of Julien transform for differentiating the perfectly synchronous shocks from the pseudo synchronous ones.

2. THE JULIEN INDEX PROCEDURE

The Julien index (JI) is the main tool used in this work to detect the shocks in order to classify them. Its calculation procedure consists in scanning, with a short window, (2n+1) time-block samples. At each time (i), the sum of the amplitudes of a time descriptor included in a window centered on i (i-n; i+n) is evaluated and compared to the ones computed on windows located to the left (i-3n-1; i-n-1) and to the right (i+n+1; i+3n+1) of the current sample (i). With excellent properties to detect shocks and fast computing time, Kurtosis has been found to be the best time descriptor for evaluating energy level of the three windows (Sassi et al, 2007). Figure (1-a) shows an example for a time sample centered at i = 15, by considering n = 2 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.

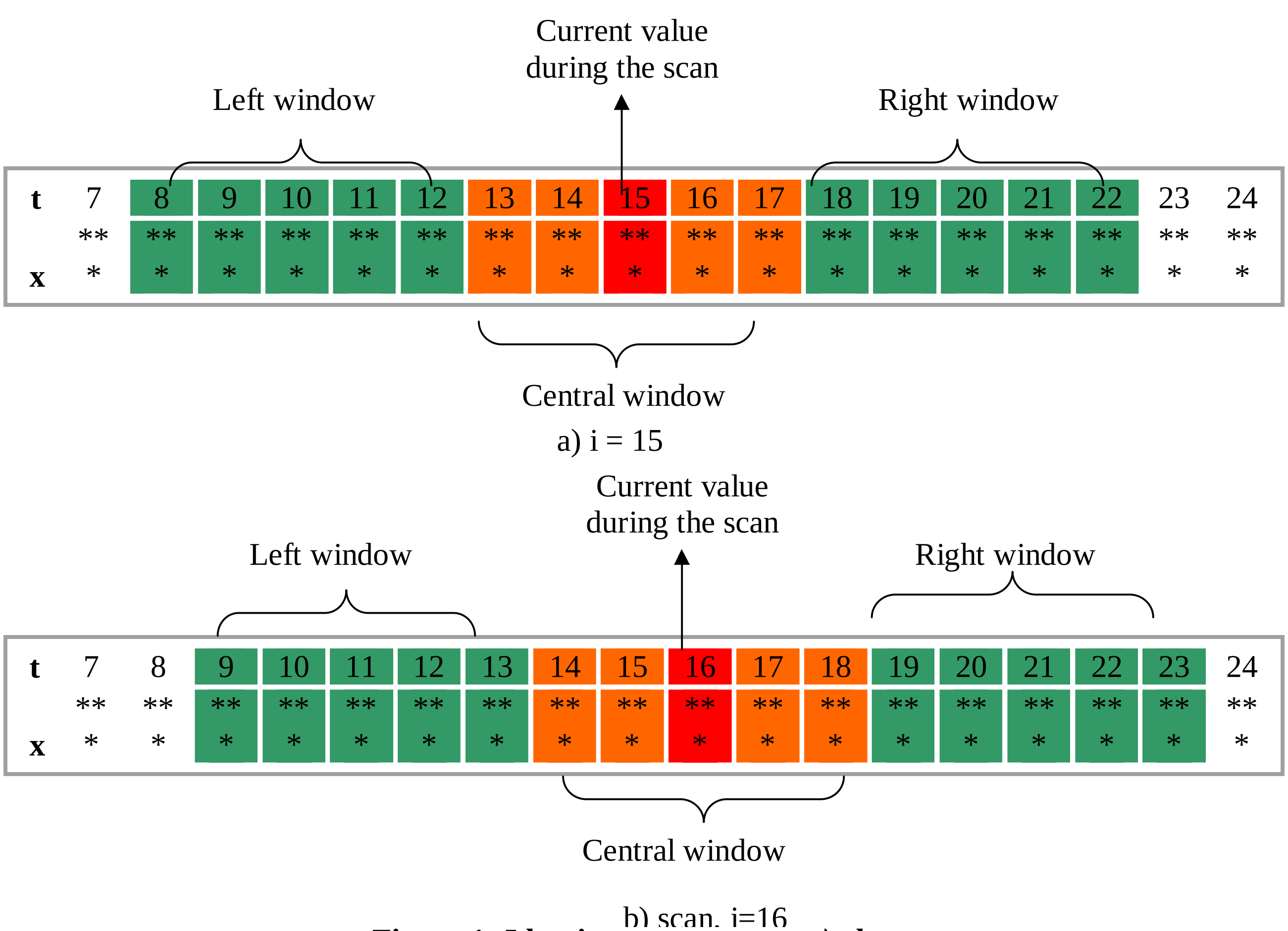

Figure 1: Identification of time windows

The amplitude of the time descriptor is computed for each of the three windows, according to the following principle:

- If the amplitude of the central window is greater than those included in the two others windows, a shock is considered and a value of 1 may be assigned to the Julien Index at position (i) : JI(i)=1.
- Otherwise, there is no shock and the Julien Index is put equal to 0 : JI(i)=0.

Then, the scan continues and the current position value is incremented to i+1 (figure 1-b). The calculation procedure will continue until the value $I = N_{max}- (3n+1)$ is reached. N_{max} is the total number of samples in the signal.

A denoising and windowing procedure is than applied to the Julien Index in order to eliminate any components of the signal other than shocks. The result is a modified time signal which contains only shocks and whose RMS value corresponds to the amplitude of the shocks present in the signal. This clean-up operation consists simply to attribute 0 to every sample where the Julien Index is 0, therefore keeping only portions of the signal where shocks are present (Fig. 2).

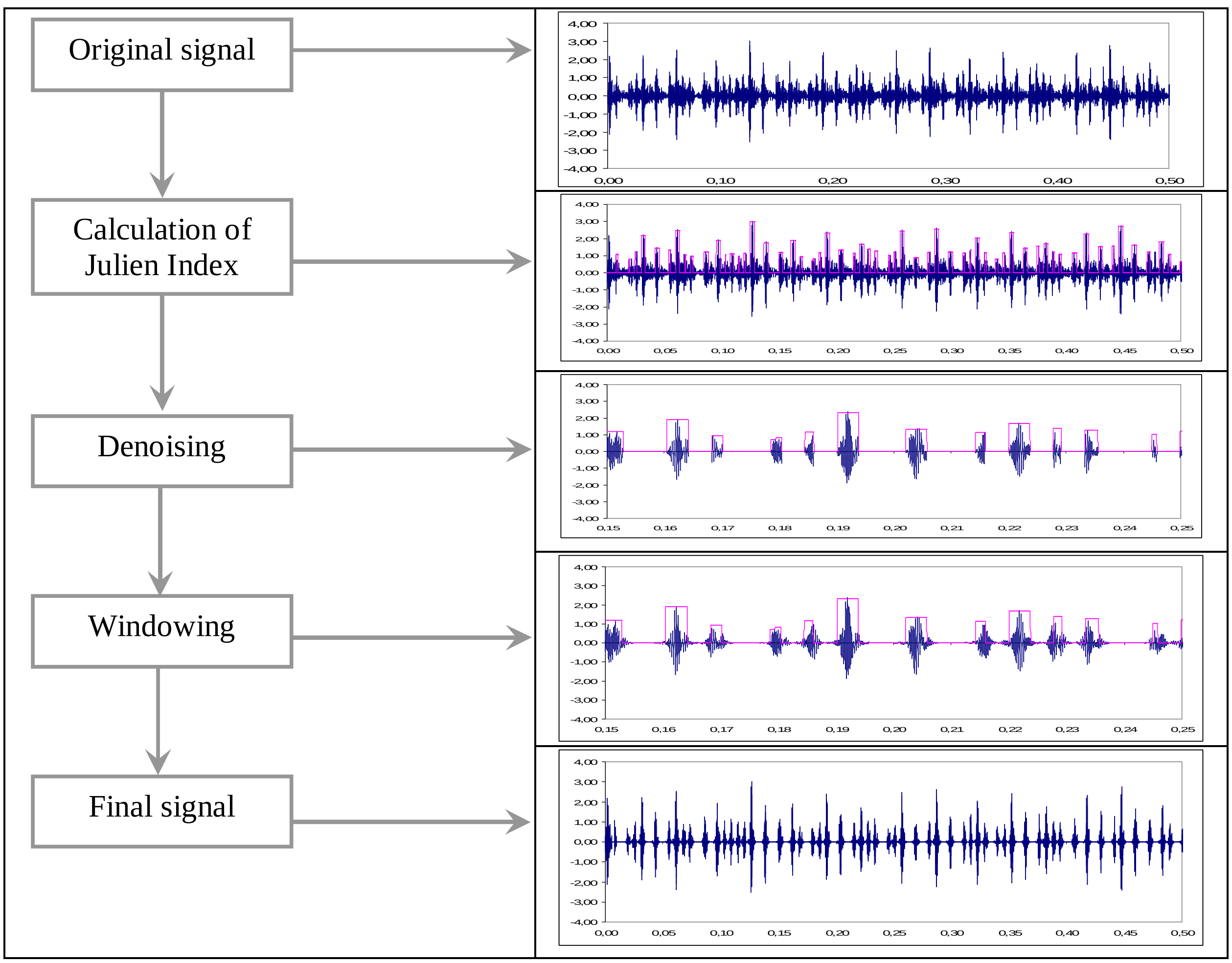

Figure 2: Julien Index Calculation

The windowing operation is necessary in order to eliminate the distortions which could appear on the Julien transform due to abrupt transitions from 0 to a sizable amplitude value (Badri et al, 2006). This windowing operation doesn't modify the energy of the refined signal. A local Hamming window is applied to each shock (RJT $\neq 0$) with a width equal to the shock length plus twice the short window length defined by the Julien Index.

The result of such procedure is the extraction of any possible shocks contained in a time signal and the elimination of the random or harmonic components. This procedure may be applied for monitoring the shock energy and leads to the definition of a signal-to-noise ratio (SNR), defined as the RMS ratio of JI on the initial signal. This procedure may be also applied for monitoring the number of shocks per period or per second.

Figure 3 shows an example of Julien Index calculation from a temporal signal extracted from a SKF 6205 bearing rotating at 1730 RPM, and containing a defect of 0.5mm on its fixed outer race.

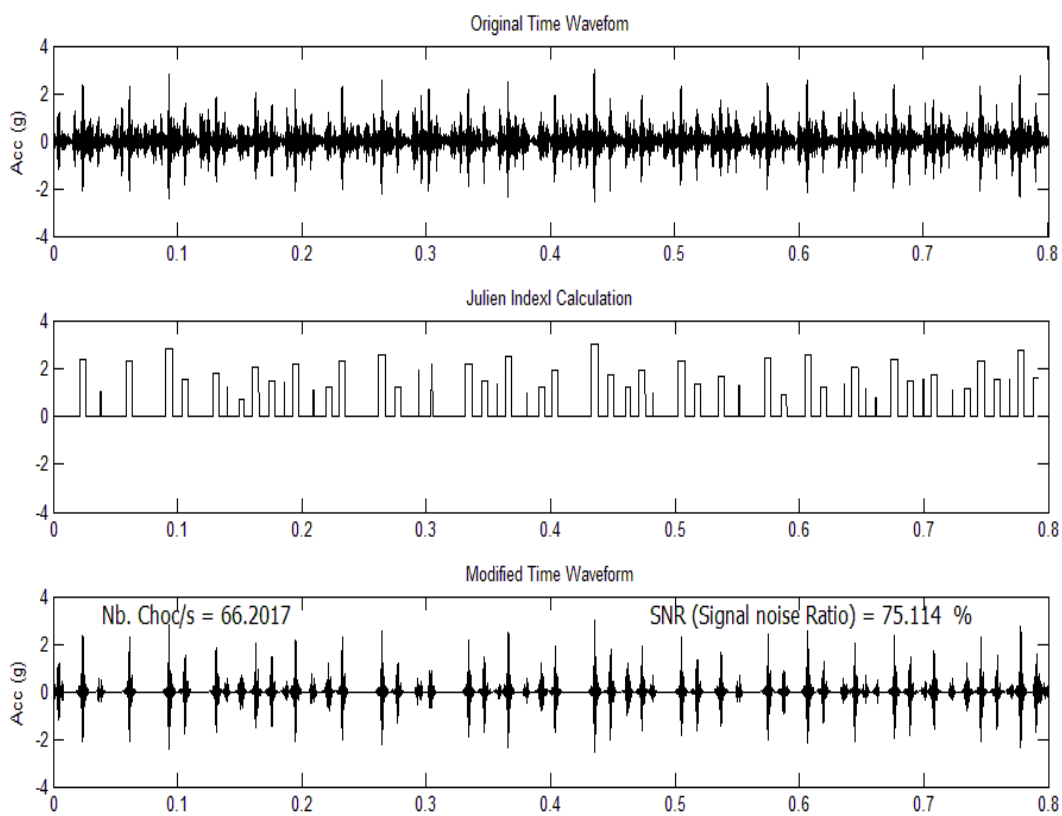

Figure 3: JI applied to an experimental bearing signal (0.72 mm on Outer race)

The Julien transform (JT) is the representation of the Julien index in the frequency domain. It permits, not only the detection of a shock and the evaluation of its energy, but also reveals the source of the defect by recognition of its frequency.

3. THE SHOCK EXTRACTOR:

The main idea behind the shock extractor is that every bearing defect (or any other regular shocking phenomena) will produce a regular (or pseudo-regular) shock pattern, and since the shock frequency is known in advance, it is possible to establish that a particular shock is related to a particular defect.

In this section, the shock extractor will be applied on two signal in order to demonstrate the separation power of this technique. The defect signal has been generated with BEAT software (BEAring Toolbox), a bearing vibration simulator developed in previous works. The following defect configuration has been considered:

- 1 Defect of 1 mm on outer race @ 0 deg (just in front of the accelerometer).
- 1 Defect of 0.8 mm on outer race at @ 180deg (diametrally opposed to the accelerometer)

3.1 Analysis

The time signal of config1 and its Julien Index are shown in Figure 4 and 5 respectively.

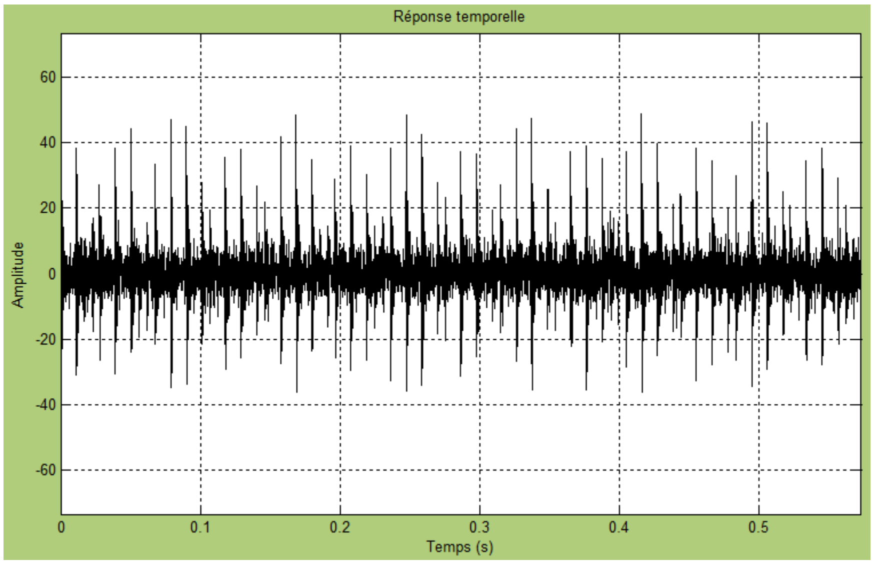

Figure 4: Time waveform of config 1 (2defects on OR)

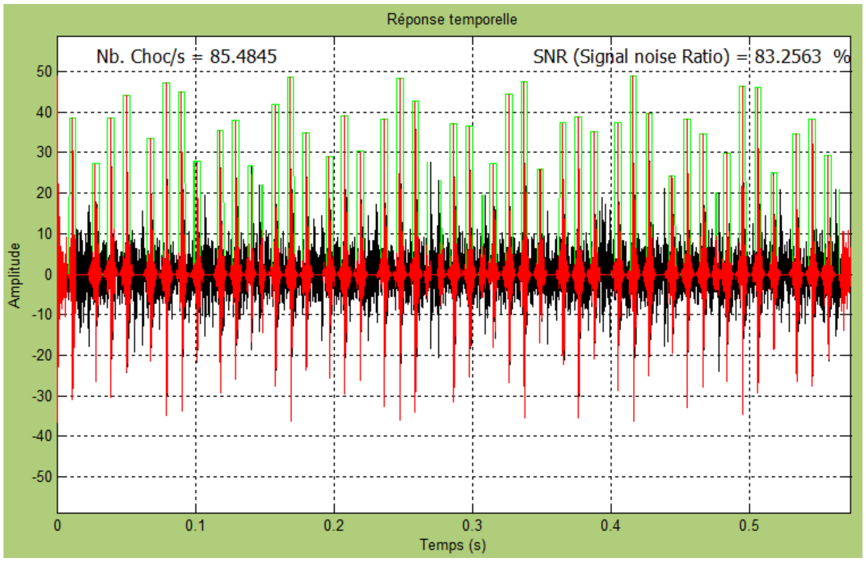

Figure 5: IJ Calculation on the original time waveform for config 1 (2defect on OR)

The IJ calculation allows for the localization and the extraction of the shock signal in the time domain. The next step is the pattern extraction of each defect. Since the defect frequency is known for the outer race, a time sweep is performed in order to detect periodic shocks forming the so called pattern using the defect period. A particular shock frequency is chosen from the envelop spectrum, which indicates the defects locations.

Fig 6 shows the application of the shock Extractor applied to the original signal. Fig 6-a shows the original time signal with two defects on outer race (1mm and 0.8 mm). The Julien index I calculation is shown in Fig 6-b). A time sweep is performed in order to extract a pattern of shocks separated by the defect period.. The first pattern is detected and marked with red *stems*. The corresponding shocks (Fig 6-c) are then isolated from the original signal by applying a local window on every shock.

This pattern is then eliminated from the JI, and the operation is performed again on the remaining signal in order to detect a possible pattern. A second pattern is detected and isolated by the same technique (Fig6-d).

As noticed, the method successfully separated each defect signal and extracted it from the original signal which contains 2 defects.

These two signals may be used to characterize each defect, by the mean of a neural network especially developed for defect recognition. The next section contains a short presentation of the neural network:

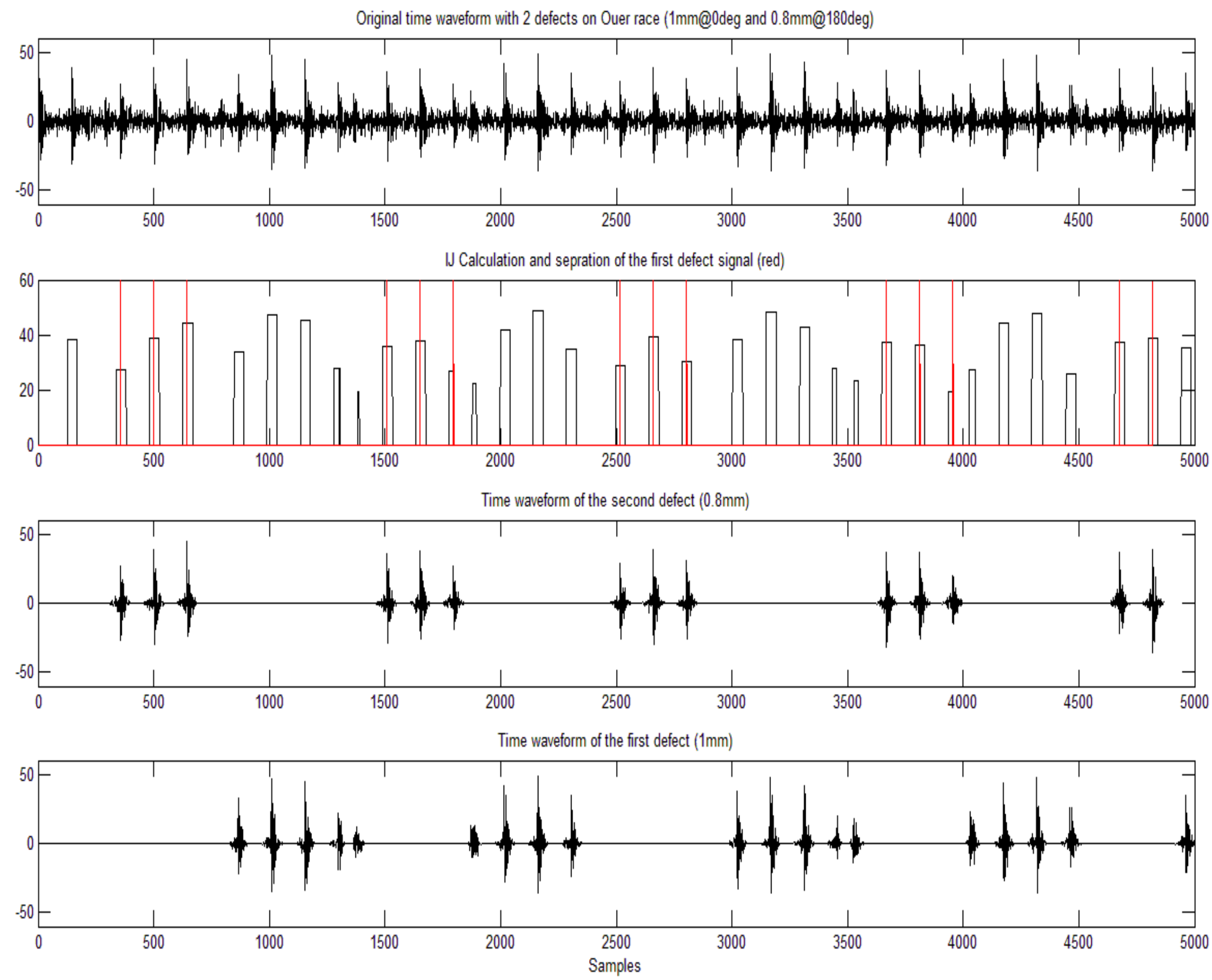

Figure 6: Shock Extractor applied to the signal 1

4. ORGANIZATION OF THE NEURAL NETWORK AND OPTIMIZATION OF THE PARAMETRES

To accomplish the ANN structure, MATLAB programming language's Neural Network toolbox was used. Training and test sessions were also done with the same toolbox. The main objective is to check the ability to recognize and quantify the location and the size of defects, by using as inputs, fault scalar indicators extracted from time domain and frequency domain signals. For this study, 3 frequency parameters (Ball Pass Frequency on Outer race, Ball Pass Frequency on Inner race and Ball Spin Frequency) have been added to six temporal parameters to form a total of nine (9) input variables (Figure 7).

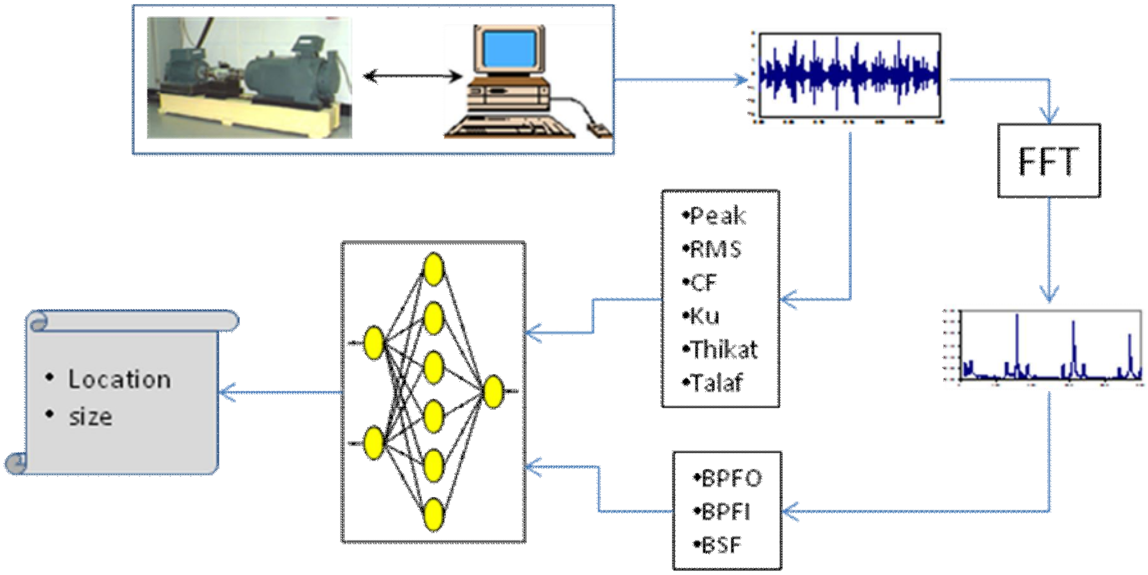

Figure 7: General layout of the ANN system

As the network configuration is a crucial step for the development of an ANN system, a trial-and-error based investigation has been conducted firstly to determine the optimum number of hidden layers and the optimum number of neurons in each layer. The retained configuration is as follows: only one intermediate layer (which is the case for numerous applications) is considered; five (5) neurons in the intermediate layer. The Log-sigmoid function was adopted as activation function.

5. RESULTS

Table1 shows the time indicators computed from the original signal and from the two identified patterns (Figure 6).

Table 1 Time scalar indicators

Time Indicators	*Original*	*1st pattern*	*2nd pattern*
Kurtosis	9.4	*28.1**	*26.2**
Crest Factor	5.6	8.2	8.9
RMS	7.5	4.7	3.2
Peak	42.7	39	28.7
Impulse Factor (IF)	8.5	26.6*	25.7*
Shape Factor (SF)	1.5	3.2	2.9

The high values obtained by computing the Kurtosis and Impulse factor of pattern signals 1 and 2 are due to the decrease of the RMS factor due to the absence of random portion of the signal. In fact, the refined signals contain only the shock portions since the method acts as a de-noising process.

The neural network has been trained with a set of 700 defects localized on outer race and 700 defects localized on inner race. The predicted values of bearing defect severity coming from the neural network are shown in Fig 8 and compared with the real values:

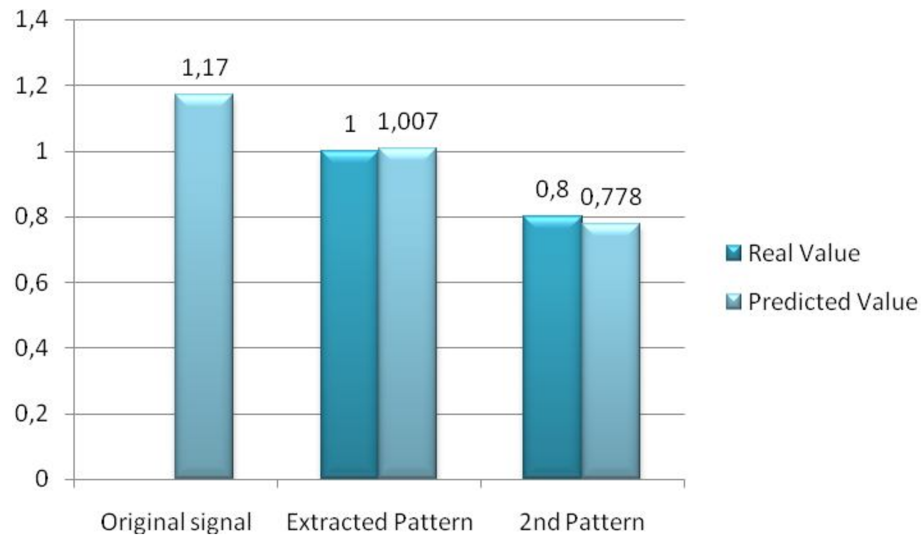

Figure 8: Real and predicted defect diameter.

Figure 8 shows that if only the original signal is directly presented to the network, the identification process will detect a single defect with 1.17 mm diameter. However, if the application is made from the extracted patterns of the shock extractor, the defect diameter may be predicted with a great accuracy (error of 0.7 % for the first defect and of 2% for the second defect) for each defect present into the signal.

6. CONCLUSION

This work presented the development of a new method, which permits to isolate shocks patterns in time domain. Signals containing multiple defects are treated, and the shock extractor is applied in order to obtain multiple signals from each defect.

The technique was associated to a neural network system in order to bypass the limitation of single defect prediction. Validation has been achieved on signals generated by a numerical simulator BEAT. The method shown its ability to identify each defect with its own severity. A maximum error of 2% has been obtained for the identification of the severity of damage.

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8. BIBLIOGRAPHY

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