FAULT DETECION IN GEARBOX USING THE WAVELET TRANSFORM

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Abstract. *This paper presents a new method of data compression using the energy of the signal in specific frequency bands, through the Wavelet Packet Transform (WPT). For this, we use an experimental bench where we collected the signs of the vibration of the gearbox with and without defects. The defects inserted in the experimetal bench were related to failures in the roller cage and the external race of the bearings. The normal condition or without defects was used for comparison with the conditions of failure. This study shows the possibility of application of WPT as an alternative technique for the extraction and compression of parameters, mainly in the diagnosis of faults introduced in rotating machinery. The formula of the Shannon entropy is used to quantify the energy of the signal in each frequency band of wavelet packet. The presence of failures in the machine indicates significantly altered levels of energy related frequencies of the defect. The results show that the analysis based on the decomposition of a signal by wavelet packet and the quantification of its energy in specific frequency bands allows the extraction and acquisition of information rather compact. These aspects are very important to control the vibration of mechanical systems, because a signal can quantify the maximum energy in the form compact and relate them to the frequency of the defect or the presence of pulses*

Keywords*: Vibration Analysis, Gearbox, Wavelet Transform.*

1. INTRODUCTION

In a scenario of growth and competitiveness, the market requires more of the industries, complex and sophisticated machines that must have a high degree of reliability. These machines should support continued work under high speed and effort. With this high level of productivity, any non-stop scheduled cause damage. Therefore, an improvement in the use of appropriate techniques of maintenance becomes essential. With a reliable system and monitoring the conditions of the machines can reduce the number of failures and unplanned maintenance activities, so that a reduction in time to stop the machines, a decrease in the cost of maintenance and operation, and consequently , an increase of the life of the equipment and the security level of components. Knowing the techniques for monitoring existing ones, improve them and develop new technologies mean a better quality of maintenance and consequently less time hours of downtime, (Brito, 2002).

Many programs for Predictive Maintenance and diagnostic systems used to condition the machine to identify and classify failures through vibration analysis (Zhang *et al*., 1996). This has been widely used in diagnosing faults and monitoring the condition of rotating machinery. What is not so widespread is the use of the Wavelet Transform, which presents itself as an excellent tool in vibration analysis, with some advantages in regard to accuracy, for the Fourier Transform. (Mamede, 1997) shows in his work results with signals measured in a gearbox, processed with the Wavelet Transform (TW). The analysis of these results shows that this tool is most appropriate for the location of components of short duration in non-stationary signals than the Fourier Transform, moreover, are used the Continuous Wavelet Transform -CWT and the Discrete Wavelet Transform with the functions Morlet, Gaussian and Deubechies.

This paper presents a methodology for data compression using the energy of the signal in specific frequency bands, through the Wavelet Packet Transform (WPT) using real signals to study and diagnose faults in bearings mounted on a gearbox. Then applies to the Wavelet Packet Transform (WPT), the analysis of stationary signals, using real data, acquired through an accelerometer mounted on a gearbox, properly mounted in the experimental bench. The fault were introduced in the roller cage and the external race of two bearings that make the gearbox. The normal condition or without defects was used for comparison with the conditions with fault. This study shows the possibility of application of WPT as an alternative technique for the extraction and compression of parameters, mainly in the diagnosis of faults introduced in a rotating machinery. The formula of the Shannon entropy is used to quantify the energy of the signal in each frequency range of the wavelet packet, which can be changed due to flaws in the machine.

The results show that the analysis based on the decomposition of a signal by Wavelet Packet and quantification of its energy in specific frequency ranges allows the extraction and acquisition of information lot compact. These aspects are very important in controlling the vibration of mechanical systems, because a signal can quantify the amount of energy and relate it with the fault frequency or presence of pulses.

2. WAVELET TRANSFORM

One of the goals of the analysis of signals is to extract relevant information from a signal, be it state or non-stationary. This is usually done using some transform. For stationary signals the spectral analysis or Fourier transform

(FT) is extremely useful because the frequency of the signal is of great importance. The Fourier transform of a signal *x(t)* is given by Eq. (2.1).

$$x(f) = \int_{-\infty}^{+\infty} x(t)e^{-i2\pi ft}\,dt \tag{2.1}$$

The analysis of the coefficients *X(f)* defines the global frequency of the signal *f(x).* Moreover, there are many non-stationary signals and transients, such as impact, shock, start and end of events, etc. These signals have characteristics that are often the most important part of the signal and Fourier Transform is not adequate to detect them (Rioul and Vetterli, 1991), (Lee *et al*., 1999). In an effort to correct this deficiency, Dennis Gabor in 1946 made the first adaptation of the Fourier transform to analyze only a small part of the signal in time (Misiti *et al*., 1997). This technique of windowing the signal is known as Short Time Fourier Transform (STFT). Mathematically, the STFT can be defined as a Fourier transform with a window in time and is a function of frequency f of the position, as Eq. (2.2).

$$STFT(f,b) = \int_{-\infty}^{+\infty} x(t)\cdot g(t-b)e^{-i2\pi ft}\,dt \tag{2.2}$$

Where *g(t)* is a window function of the signal *x(t),* whose position is shifted in time. The STFT transform a signal in time domain in a two-dimensional function in time-frequency *(f, b),* which can be represented by a spectrum.

There are some limitations associated with the STFT. One relates to the width of the window, whose value is constant for all frequencies, as shown in Fig. 2.1 (a). A large window (more samples) allows a good resolution in the frequency domain, but poor resolution in time domain and vice versa (Misiti *et al*., 1997). Then, the STFT is not possible to obtain a good resolution in time domain and frequency, simultaneously. Thus, the Fourier Transform of short-time introduces a scale, which is given by the width of the window, and analyzes the signal from the point of view of the scale. If the signal has important details out of scale, have problems in the analysis.

To resolve this problem of the Fourier Transform of short duration, you must define a transformation that is independent of scale. This transform not use a fixed scale in the analysis, but vary the scale to avoid commitment to a specific scale. This is known as Wavelet Transform (WT). It allows a signal is analyzed with good resolution in time or frequency, as shown in Fig. 2.1 (b). For example, to close a window, it has a good resolution in time and low resolution in frequency. Moreover, a large window, it has good resolution in frequency and low resolution in time.

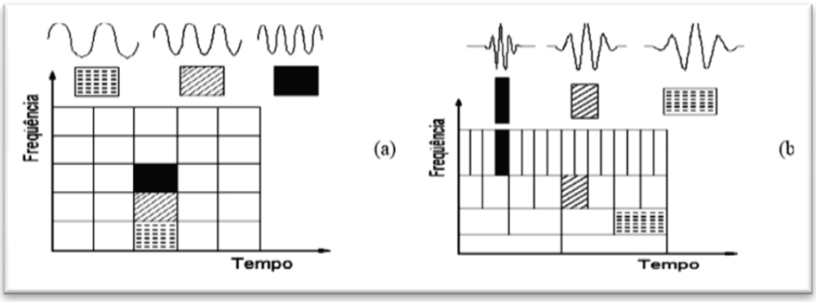


Figure 2.1 - Time-frequency resolutions of (a) STFT and (b) CWT (Santiago, 2004).

The Wavelet Transform of (WT) is an improvement on the STFT because use is a technique that scales variables. The wavelet analysis allows the use of a smaller scale, when you want higher resolution of the information contained in the high frequency signal, and a larger scale when you want higher resolution of the information contained in the signal at low frequency. The frequency and scale quantities are inversely related, that is, a smaller scale implies a high frequency and vice and it turns (Staszewski and Tomlinson, 1994) and (Satish, 1998).

The concept of scale in WT was introduced as an alternative to frequency, leading it to a breakdown of time and scale. This means that a signal can be mapped according to the scale and time. This is equivalent to mapping time and frequency, used in the STFT, through a spectrum. In fact, there is a correlation between the scale and frequency and wavelet transform may be regarded as a representation in time-frequency (Mori *et al*., 1996), (Ruzzene *et al*., 1997) and (Adewusi and Al-Bedoor, 2001). But which would be ultimately a wavelet? A wavelet is a wave of limited duration and has an average value equal to zero. The inevitable comparison is the original of a wavelet with a s sinusoidal, which is the basis of Fourier analysis. Sinusoidal are unlimited in time - they run from - ∞ to + ∞.

Moreover, while sinusoidal are smooth and predictable, wavelets tend to be irregular and asymmetric. Fig. 2.2 illustrates these differences.

Figure 2.2 - Comparison between a sinusoidal and a wavelet (db10) (Misiti *et al*., 1997)

The analysis of Fourier is to decompose a signal in sinusoidal waves of various frequencies. Similarly, the analysis by wavelets is the decomposition of a signal in versions "displaced" and "spread" of the original wavelet (or mother wavelet). To see pictures of waves and wavelets sinusoidal, as illustrated in Fig. 2.2, it appears intuitively that signals with abrupt changes are potentially better analyzed with a typical and irregular wavelet than with a soft sinusoidal. Formally speaking, the majority of wavelets functions of interest are called "localized" both in time and in scale (frequency).

This is characteristic of wavelets which enables applications such as compression of the signal, the focus of analysis for a specific region of the spectrum variant of interest in time, or the location of areas of greatest concentration of energy, among others. The analytical treatment for the analysis of wavelets includes the continuous wavelet transform and the discrete, and their inverse transformed. The continuous transform brings a great redundancy of information on the signal analysis, which makes it computationally uninteresting. The discrete transform is used, whether in its simplest version the *multiresolution analysis* is the version that allows for custom detailing the spectrum, which is the analysis by packets.

2.1. Continuous Wavelet Transform

The Continuous Wavelet Transform (CWT) of a signal *x(t)* is defined by Eq. (2.3).

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t).\psi^*{}_{a,b}(t)\,dt,\;\; a \text{ e } b\ \in \mathbb{R}, a \neq 0 \tag{2.3}$$

Where $\psi(t)$ is the mother wavelet, ψ * is the complex conjugate of $\psi(t)$ and $\psi_{a,b}(t) = 1 / \sqrt{|a|}\psi\big((t-b)/a\big)$ are wavelets *daughters*. The parameter *a*, called the scale, spread a function of compression or expansion, and *b* is the same as the STFT called the coefficient of translational and simply advances or retards the position of the wavelet in the time axis. The basic difference between the STFT and CWT CWT is that the use is a scale variable instead of a variable frequency in the STFT. Mathematically a delay function *f(t)* t_d of means represent it by f (t-t_d). The factor $1 / \sqrt{|a|}$ is used to ensure that the energy of the wavelets is staggered by a factor of the same mother wavelet (Chan, 1996), (Chen *et al*., 1999).

The results of the CWT are many wavelet coefficients C, which are a function of scale and position. Multiplying it by each wavelet coefficient corresponds appropriately scaled and shifted, we obtain the constituent wavelets of the original signal, as shown in Fig. 2.3:

Figure 2.3 - Decomposition of a signal into its constituent components by CWT wavelets.

The analysis by wavelets produces a long-range vision of a signal. As previously mentioned, the scales have an inverse association with the frequency of a signal. Basically, a wavelet scaling means stretch it or compress it. If the wavelet function is defined as a sinusoidal of frequency ω, for example, there is easily that the scale factor is exactly the inverse of ω. In general, therefore, the scale is related to the frequency content of the signal analysis by wavelets.

Therefore, the CWT is the sum over the entire time domain signal by multiplying the staggered and displaced versions of a properly chosen wavelet. This process produces wavelet coefficients C which is a function of scale and position (time). The higher C is, the more the similarity. More precisely, if the signal energy and the wavelet energy are equal to one, C may be interpreted as a correlation coefficient.

More precisely, if the energy of the signal and wavelet are energy unit, C can be interpreted as a correlation coefficient. Obviously the results depend on the shape of the wavelet chosen. The coefficients calculated for the different scales in different sections of the signal should be grouped in orderly manner, particularly when you wish to view these results on a graph.

2.2. Wavelet Packet Analysis

In the calculation of the CWT parameter scale and position changes continuously. However, the calculation of the wavelet coefficients for every possible scale can represent a considerable effort computational and a very large amount of data to be analyzed later.

Thus, the use of the Discrete Wavelet Transform (DWT) becomes important because it allows the discretization of the wavelet scale based of two, that is in the scale, called a dyadic scale. Use this scale makes the implementation faster computing and data analysis very efficient. Therefore, the parameters *a* and *b* of Eq. (2.3) is replaced by 2^j and $k2_j$ respectively, and the DWT is defined by (Chui, 1992), as Eq. (2.4).

$$DWT(j,k) = \int_{-\infty}^{\infty} x(t).\psi^*{}_{j,k}(t)dt, \;\; j \; e \; k \in \mathbb{Z} \tag{2.4}$$

Where, $\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}.\psi\left((t-k2^j)/2^j\right)$ are functions orthogonal wavelets, which constitute a basis of L^2 (R) (Daubechies, 1988). Similar to the Fast Fourier Transform (FFT), there is an algorithm for implementation of DWT based on the rapid decomposition of Wavelet Transform (FWT), which is normally used and known as *Multiresolution Analysis* (MRA) of Mallat pyramid algorithm or the which was developed by Mallat in 1988 (Misiti *et al.*, 1997), (Mallat, 1989). This algorithm uses a special filtering process to decompose the signal, where the contents of the low frequency signal is called the approximation, and the high frequency is called the detail. This process of filtering decomposes the original signal into approximations and details, and can be interpreted as low-pass filters and high-pass, respectively, as shown in Fig. 2.4.

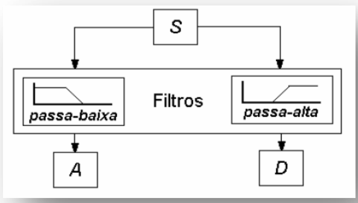


Figure 2.4 - Schematic diagram of the multiresolution analysis (Santiago, 2003).

The multiresolution analysis consists of decomposing a signal in j-th levels or resolutions. The wavelet function $\psi_{(j,k)}(t)$ is correlated with a high-pass filter to provide the detail (coefficients) of the signal at different levels. In the multiresolution analysis is an additional function $\varphi_{(j,k)}(t)$, called a function of scale, which is correlated with the low-pass filter to provide approximations of the signal at different levels. When j = 0, $\varphi_{(j,k)}(t)$ is the same as the original signal. In this analysis, is called the approximation and detail signal as Eq. (2.5) and Eq. (2.6).

$$A_j[x(t)] = x(t)^*\phi_{j,k}(t) \tag{2.5}$$

$$D_j[x(t)] = x(t)^*\psi_{j,k}(t) \tag{2.6}$$

Where, $\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}.\psi\left((t-k2^j)/2^j\right)$ are orthogonal functions of scale and * denotes the convolution operation. How, $\varphi_{(j,k)}(t)$ and $\psi_{(j,k)}$ (t) are correlated through a pair of filters *g(t)* and *h*(t), they can be defined by Eq. (2.7) and Eq. (2.8).

$$\phi_{j,k}(t) = h(t)^*\phi_{j-1,k}(t) \tag{2.7}$$

$$\psi_{j,k}(t) = g(t)^*\phi_{j-1,k}(t) \tag{2.8}$$

Solving *g(t)* and *h(*t) of Eq. (2.9) and Eq. (2.10) combining with equations (2.7) and (2.8) is obtained by the DWT:

$$A_j[x(t)] = h(t)^* A_{j-1}[x(t)] \tag{2.9}$$

$$D_j[x(t)] = g(t)^* A_{j-1}[x(t)] \tag{2.10}$$

Or, rewriting them with other notation is obtained by the Eq. (2.11), Eq. (2.10), and Eq. (2.13)

$$A_0[x(t)] = x(t) \tag{2.11}$$

$$A_j[x(t)] = \sum_n H(n-2t)^* A_{j-1}[x(t)] \tag{2.12}$$

$$D_j[x(t)] = \sum_n G(n-2t)^* A_{j-1}[x(t)] \tag{2.13}$$

The calculation of the DWT is done using these expressions of decomposition of the signal, which are obtained with the Mallat algorithm based on multiresolution analysis. Where, $n = 1,2 ..., N$ and $j = 1,2, .. J$, $H(n)$ and $G(n)$ are low-pass filters and high-pass, respectively (Wu and Du, 1996). In short, the theory of multiresolution can decompose a signal as follows: first, an original discrete signal at the first level is decomposed into two components *A1* and *D1* for a low-pass filter and a high-pass, respectively.

The *A1* is called the approximation signal and *D1*, is called the *detail* signal. For the second level, the approximation *A1*, is now split into a new approximation *A2*, and a detail *D2*. This procedure can be repeated for the third level, fourth, etc. Figure 2.5 shows the tree of the wavelet decomposition of a signal at three levels. A type of wavelet often used in the calculation of DWT of a signal, based on analysis of multiresolution is the wavelet of Daubechies.

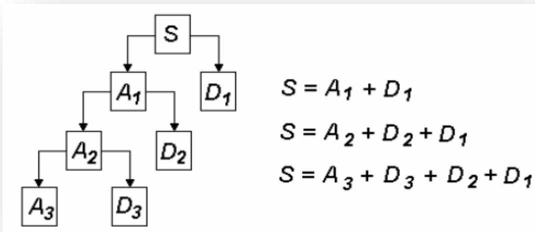


Figure 2.5 - Tree of the wavelet decomposition of a signal at three levels (Santiago, 2003).

Furthermore, the Wavelet Packet Transform (WPT) is a generalization of the discrete wavelet transform. While the DWT shown in Fig. 2.6 (a) decomposes the signal only at low frequencies, the WPT shown in Fig. 2.6 (b) breaks the signal into low and high frequencies. Each vector A_j has $N_t / 2^j$ coefficients, where N_t is the length of the signal S, and provides information about a frequency band of $[0, F_s / 2^{j+1}]$, and is the sampling frequency of the signal . Each node or packet WPT is indexed by a pair of integers *(j, k)*, where *j* is the corresponding level of decomposition and k is the order of the position of packet in a particular level. At each level *j*, we have 2_j and your order is $k = 1,2 ..., 2j-1$. For example, at $j = 3$ there are three 8 knots or packets. A vector of coefficients $c_{j,\,k}$ is the wavelet packet to each packet *(j, k)* and its length is approximately $N_t / 2^j$.

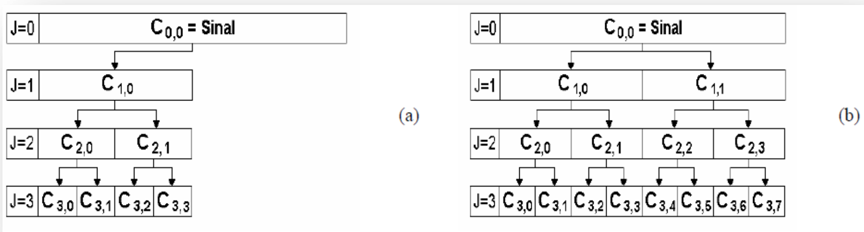


Figure 2.6 - Decomposition of the original signal with, (a) DWT and (b) Wavelet Packet.

Looking to Figure 2.6 (b), the vectors $c_{j,k}$ contains information of the original signal into different frequency bands. For example, if the sampling frequency of the signal is *16000 Hz*, then the frequency band of analysis related to the vector $c_{0,0}$ is *0-8000 Hz*. For $c_{1,0}$, *0-4000 Hz* for $c_{1,0}$, *4000 -8000 Hz* and $c_{3,0}$, *0-1000 Hz*, and so on. One advantage of the WPT for the decomposition of the signal is that it can analyze the information contained in the sign, whether stationary or non-stationary at different time-frequency resolutions. Another advantage of WPT concerns the compression of information in the signal. For example, for $j=3$ $N_t = 1024$ samples, the vector $c_{3,0}$ has $N_t / 2^j = 128$ samples and the same frequency band of *0-1000 Hz*.

Note that each packet $c_{j,k}$ WPT retaining information of the original signal in a compact. This fact is very important in analysis and signal processing, especially in diagnosis of failures, they can retain information only on the signal frequency band where the frequencies of failure appear. In practice, usually choose the packets that it retains more information if the original signal and discards the packets containing less important information and noise. For this, we use some criteria for selection of optimal packets. A widely used criterion is the criterion based on the quantification of energy in the signal (Scheffer and Heyns, 2001).

In this work, it used the standard formula of the Shannon entropy to estimate the energy in the signal and each node of wavelet packet (Misiti *et al.*, 1997), which is given by Eq. (2.14), where *s* is the signal and the sample itself is the signal at time *i*:

$$E_n(s) = -\sum_i s_i^2 \log (s_i)^2 \tag{2.14}$$

It was concluded that the implementation of the Wavelet Packet Transform based on the quantification of the original signal energy in specific frequency bands allows the extraction and retrieval of information rather compact. As we shall see below.

3. EXPERIMANTAL ANALYSIS

This section presents a methodology for data compression using the energy of the signal in specific frequency bands, through the Wavelet Packet Transform (WPT), the analysis of stationary signals, using real data. This study shows the possibility of application of WPT as an alternative technique for the extraction and compression of parameters, mainly in the diagnosis of faults introduced in rotating machinery.

For this study, we used the experimental bench shown in Fig. 3.1. The experimental bench consists of a gearbox Flender SZN – 112[3], which is driven by electric motor[1] powered by a frequency inverter WEG CFW 09 with the rotation frequency of about 30.32 Hz and gearbox the engine is coupled through a flexible coupling of Flender [2] the mechanical brake Twiflex of Tec Tor [4] is mounted on the output shaft of the reducer and acts as system load and is driven manually.

Figure 3.1 - Experimental bench.

The signs of vibration were collected for the accelerometer CMSS2200 SKF, and processed by the acquisition card of National Instruments model NIcRio-9215 and were finally analyzed in the Wavelet Toolbox of Matlab software. Bearings 33205 (SKF) and 30211J2 (SKF), mounted on the gearbox were replaced by two others of the same model, but had a defect in the roller cage and the external race. The normal condition or without defects was considered, for purpose of comparison. Figure 3.2, Fig. 3.3 and Fig. 3.4 show the spectra in acceleration envelope of the bearing 30211J2 (SKF) in perfect condition, with the same defect in the roller cage and roller 30211J2 (SKF) with external defects on external race, respectively.

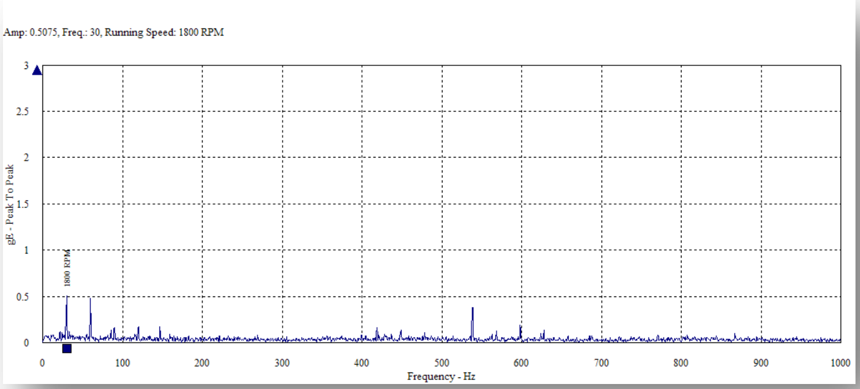


Figure 3.2 - Envelope of acceleration of the bearing 30211J2 (SKF) in normal (no defect).

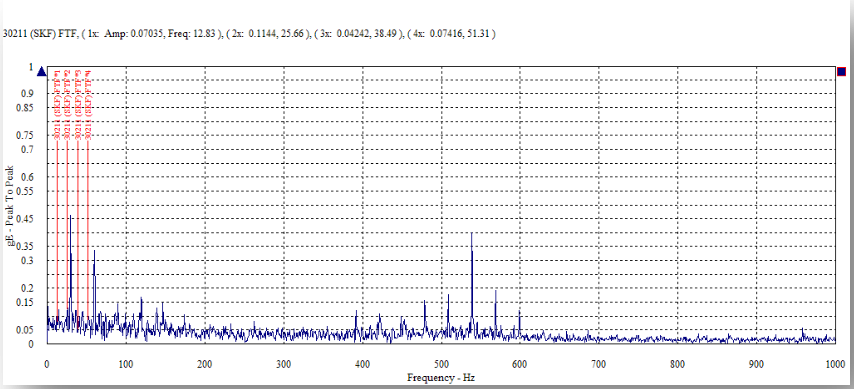


Figure 3.3 - Envelope of acceleration of the bearing 30211J2 (SKF) with defects in the roller cage.

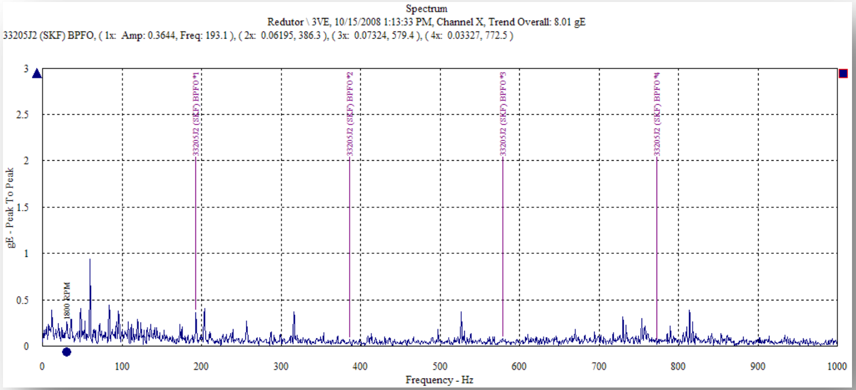
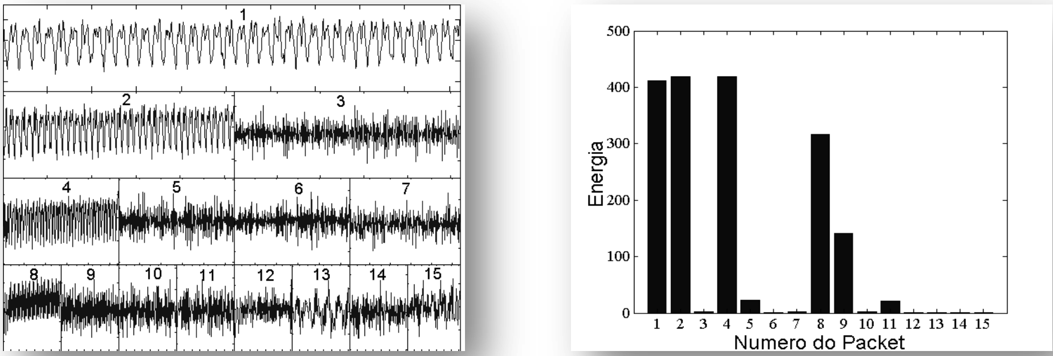


Figure 3.4 - Envelope of acceleration of the bearing 33205J2 (SKF) with defects in the external race.

In normal condition, Fig. 3.5 (a) shows the packet 1, the original signal composed of frequencies equal to 1x, 2x, 3x, 4x etc.. Is the packet 3, which shows only the signal shown in the high frequency components and Figure 3.5 (b) there is such a machine excited frequencies with little energy. Figure. 3.5 (b) shows a representation of the global distribution of energy in all frequency bands specific. Observe that the energy contained in packets 2, 4 and 8 are higher because they relate to the frequency of rotation of the gearbox. While the energy contained in paragraph 9 relates to the harmonic 2x.

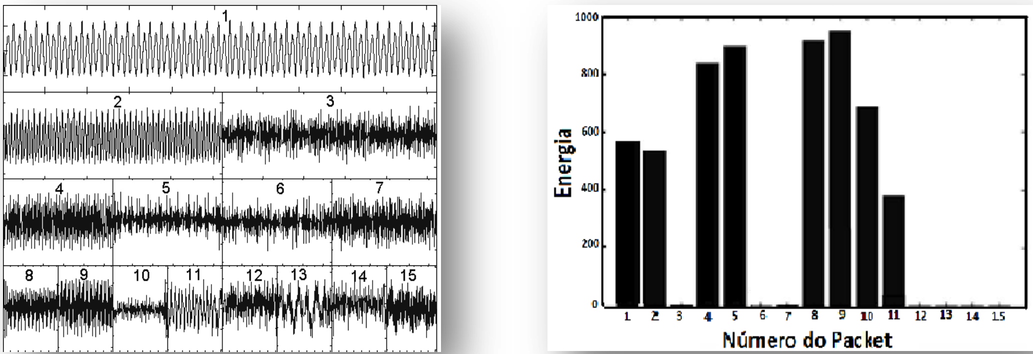


(a) (b)

Figure 3.5 - Normal condition, (a) Wavelet Packet and (b) Power Distribution.

Similarly, the Fig. 3.6 (a) and Fig. 3.6 (b) show the wavelet packet and distribution of energy to the already bearing 30211J2 (SKF) showing failure in the roller cage. Who determines which are the deterministic frequencies of failure of a bearing, is frequency of rotation of equipment and their fundamental frequencies, which are provided by the manufacturer of bearings. These two determine which frequencies will be excited by a particular type of failure. It is in this case, a defect in the roller cage 30211J2 SKF, the deterministic frequency of failure are formed by the *frequency of rotation x 0.42225,* and the harmonics of the product, where 0.422252 is fundamental frequency of failure for this bearing in specific. The frequency of rotation that reaches the gearbox is approximately 30.38 Hz, ie, using the calculations above we come to the following frequencies of deterministic fault: 12.83 Hz, 25.66 Hz, 38.49 Hz and 51.31 Hz .

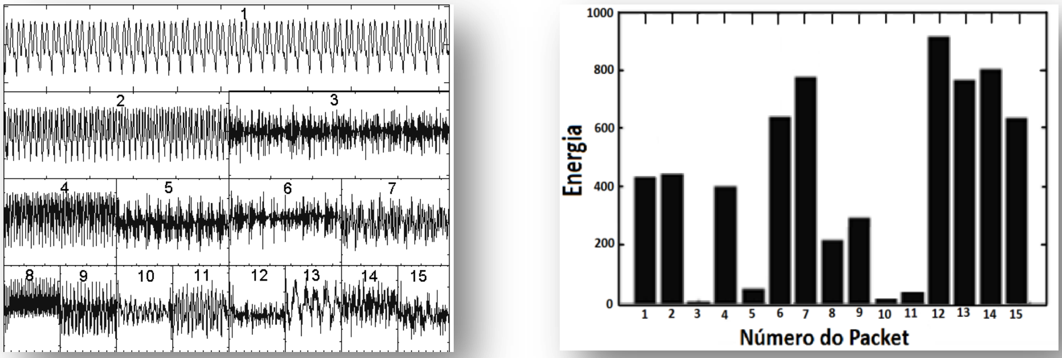
Therefore, if the level of energy present in at least one of the frequencies above are changed, there is a great sign of failure in the roller cage. Figure 3.6 (b) shows that the level of energy in our 4, 5, 8, 9,10 e 11, which correspond to packets that include the frequencies that indicate failures are relatively changed in comparison with the situation without defect. This shows how failures change the energy level of nodes associated with the frequency of excitation.



(a) (b)

Figure 3.6 - Fault of the roller cage, bearing 30211J2(SKF); (a) Wavelet Packet and (b) Power Distribution.

Finally, are represented in Figures 3.7 (a) and 3.7 (b) the wavelet packet and distribution of energy due to the fault in external race -33205J2 SKF bearing. They determine which frequencies will be excited by a particular type of fault. There is this case of a defect in the external race of the bearing, the deterministic frequency of fault are formed by the *frequency of rotation x 6.36873* and the harmonics of the product, where 6.36873 is the characteristic frequencies of fault in the runway for foreign bearing in question. As the frequency of rotation of the reduction of approximately 30.38 Hz, the above calculations result in the following frequencies of deterministic fault: 193.482 Hz, 386.964 Hz, 580.446 Hz and 773.928 Hz So if the level of energy present in at least one of frequencies above there are indications of a possible defect in the bearing. Figure 3.7 (b) shows that the level of energy present in our 6, 7, 12, 13,14 and 15, which correspond to those that include the frequencies that indicate failures are relatively high. This shows how failures change the energy level of packets associated with the frequency of excitation.



(a) (b)

Figura 3.7 - Fault external race, bearing 33205J2(SKF); (a) Wavelet Packet and (b) Power Distribution.

3. CONCLUSION

The results show that the analysis based on the decomposition of a signal through the Wavelet Packet Transform (WPT) and in the quantification of energy of the signal in specific frequency bands allows the extraction and retrieval of information rather compact. These aspects are very important, first, to monitor the vibration of mechanical systems, because one can quantify the maximum signal energy in the form of compact and relate them to frequency of the defect or the presence of pulses, second, on tasks recognition of patterns with applications in neural networks. The WPT retains the original signal information so compact.

This fact is very important in analysis and signal processing, especially in the diagnosis of faults, because you can retain information only on the signal frequency band where the frequencies of the faults appears. In practice, usually choose the packets that it retains more information if the original signal and discards the packets that contain noise and less important information. In this work, presents a new methodology for diagnosis of faults in rotating machinery. Finally, was the possibility of practical applications of this work in aid, for example, the predictive maintenance of equipment, and through monitoring of their conditions of operation predict and diagnose possible faults not desirable.

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