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Gear Fault Diagnosis Across Autocorrelation of Optimal Wavelet Transforms

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Abstract— **The fault diagnosis of rotating machinery has attracted considerable research attention in recent years and many publications have been seen in this field. Monitoring and fault diagnosis methods based on signal processing have proved effective in fault identification. A novel method based on autocorrelation of an optimal wavelet transform is proposed for the analysis of vibration signals produced from a gear system under test in order to early detect the presence of faults. An early indication of the presence of a gear defect is obtained at the 10th day of experimentation before the tooth damage.**

***Keywords*— Early Fault detection, Autocorrelation, wavelet transform.**

I. Introduction

Monitoring and fault diagnostics is useful for ensuring the safe running of machines. Gears are widely used in rotating machines and often subjected to harsh working conditions. Therefore, they have received a lot of attention in the field of vibration analysis as they represent a common source of fault and one of the key issues is to capture the signal transients.

Signal processing is an approach widely used for monitoring and fault diagnostics, whose aim is to find a simple and effective signature of the defect. Therefore, a proper signal processing method is needed.

The most popular signal processing methods for bearing vibration analysis is envelope analysis, by which the vibration signal is first operated through a band-pass filter to obtain a high signal-to-noise ratio signal, and then Hilbert transform is used to obtain the envelope. If periodic impulses appear in the envelope, which correspond to bearing characteristic frequency, then it can be inferred that the bearing is under fault condition [1-2].

The important information and the dominant features contained in the signals can be extracted in order to detect faults in gear systems. Since the vibration signals delivered from gears contain non-stationary components due to gear faults, we must find robust signal processing methods to analyse the non stationary vibration signal [3].

To deal with non-stationary signals, several time frequency and time scale technique analysis were developed such as the short-time Fourier transform (STFT), Wigner-Ville distribution (WVD) or wavelet transform (WT) [4,5].

Due to the poor working conditions, early gear failure information has largely been submerged in the interference of noisy signals. The frequency and time signals from different failures such as wear and tooth broken are quite similar, which makes it difficult to diagnose them directly in time domain or frequency domain. In the time domain analysis, for example, a gearbox fault is detected by monitoring the variation of some statistical indices such as a root mean square value, crest factor or kurtosis [6].

At present, several types of advanced signal processing techniques have been proposed in this field [7-16]. Among these techniques the wavelet transform has been introduced. Wavelet transform is another popular signal processing method for bearing fault diagnosis, due to its flexile time–frequency resolution and excellent capability of detecting transients. The transient characteristics of wavelets can be employed to carry out accurate and effective analysis of signals with complex frequency time structure [17]. Wavelets transform is capable of processing stationary and non-stationary signals in both time and frequency domains. This important approach is increasingly used in condition monitoring.

However, due to large interference detection signal, it's still difficult to search for singularity of wavelet transform; therefore the autocorrelation analysis is used in the precise positioning to failure.

This paper introduces a simple method based on the autocorrelation function of wavelet coefficients. This method is applied in order to diagnosis bearing fault to achieve high consistency and detect fault in early stage.

The remaining of this paper is organized as follows: First, the theoretical background of the method used in section 2. The proposed method is applied in order to early detect the fault of real gear systems in Section 3. Finally, in section 5, we give a general conclusion.

II. Theoretical Background

A. Wavelet transform

The wavelet transform represents the signal as a sum of wavelets at different locations (position) and scales (duration). The wavelet coefficients work as weights of the wavelets to represent the signal at these locations and scales.

The wavelet transform is accomplished using the translated and scaled versions of a mother wavelet $\psi(x)$ defined by:

$$\psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

Where (a) and (b) are scaling (dilation) and translation parameters, respectively.

The mother wavelet ψ (t) by dilated (parameter b) and translated (parameter a) is designed to balance between the time domain and frequency domain resolution. We can see clearly very low frequency components at large b, which makes the width of the mother wavelet expansive, and very high frequency components at small b, which makes the width of the mother wavelet concentrating [17-19].

The wavelet transform of signal x(t) is defined as:

$$C(a,b) = |a|^{-1/2}\int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \quad (2)$$

Where $C(a,b)$ denote the wavelet coefficients of signal x(t).

(*) is a symbol of a complex conjugate function.

There are different types of mother wavelet functions for different purposes, such as the Haar, Daubechies, Gaussian, Meyer, Mexican Hat, Morlet, Coiflet, Symlet, Biorthogonal and so on. The oldest and most basic of the wavelet systems is the Haar wavelet that is a group of square waves with magnitude of ±1 in the interval [0,1]. This kind of wavelet is conceptually simple and fast, and is particularly suitable for the analysis of signals with sudden transitions. Therefore, The Haar wavelet was adopted.

The Haar wavelet's mother function $\psi(t)$, shown in Fig.1, is defined for $t \in [0,1]$ as follows:

$$\psi_0(t) = 1$$

$$\psi_1(t) = \begin{cases} 1, & 0 \le t \le 0{,}5 \\ -1, & 0{,}5 < t \le 1 \end{cases} \quad (3)$$

And $\psi_i(t) = \psi_1(2^j t - k)$ for $(i > 1)$ and we write $(i = 2^j + k)$ for $j \ge 0$ and $0 \le k \le 2^j$. We can easily see that the $\psi_0(t)$ and $\psi_1(t)$ are compactly supported; they give a local description, at different scales j, of the considered function [20].

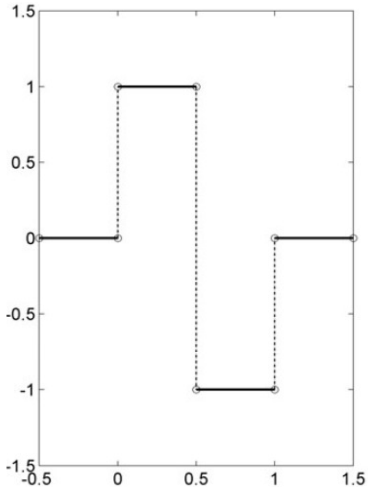

Fig. 1. Diagram of the Haar's wavelet mother function.

B. Autocorrelation coefficients

In signal processing, the processes whose statistical characteristics vary periodically with time are called cyclostationary processes. Nonstationary signals are considered cyclostationary when some of their statistics are periodic [21]:

$$f_x(x,t) = f_x(x,t+T) \quad (4)$$

Where $f_x(x,t)$ denotes some appropriate, time varying, statistic of the signal.

The vibration signals of rotating machinery consist of random and periodic components. Their autocorrelation function exhibits a time-varying, periodic and cyclostationary character. The autocorrelation function is suggested to enhance the periodicity of the fault signature [22].

The autocorrelation presents a better understanding of the evolution of a process through time using the probability of the relationship between data values separated by a specific number of time steps (lags) [22-25].

For a signal $x(t)$, the autocorrelation function $R_x(t)$ is generally defined as the continuous cross-correlation integral of $x(t)$ with itself, at lag τ.

The cross-correlation function of signal $x(t)$ and $y(t)$ is defined as:

$$R_{xy}(t) = \sum_{n=0}^{\infty} x(n)y(n+r) \quad (5)$$

Equation (5) expresses that the sum of $\sum_{n=0}^{\infty} x(n)$ multiply $y(n+r)$, which is $y(n)$ for r sampling points left. If x(n) =

$y(n)$, equation (5) defining the cross-correlation function becomes the autocorrelation function.

$$R_x(t) = E[x(t), x(t-\tau)] \qquad (6)$$

Where (τ) is a time lag.
E[,] denotes the mathematical expectation operator.

For processes that are also ergodic, the expectation can be replaced by the limit of a time average. The autocorrelation of an ergodic process is defined as:

$$R_x(t) = \lim_{T\to\infty} \int_0^T x(t).x(t+\tau)dt \qquad (7)$$

The autocorrelation function reaches its peak at the origin, where it takes a real value, i.e. at any lag τ:

$$|R_x(\tau)| \leq |R_x(0)| \qquad (8)$$

III. RESULTS AND DISCUSSIONS

The vibration signals of the gear reductor under study have been provided from CETIM (Centre d'Etudes Techniques des Industries Mécaniques, 52 av. Felix Louat, 60300 Senlis, France) [26-29]. They are delivered from a reductor operating 24 hours over 24 hours. The dimensions of gear wheels together with the operating conditions (speed, couple) are adjusted so that we obtain a spalling on all the width of a tooth. During experimentation, the system has been stopped every day to observe the state of the wheel teeth.

The gear system consists of two wheels with respectively 20 and 21 teeth. This system operates under fixed conditions 24h/24h.

The rotational frequencies of the two wheels are in the range of 16.67 Hz and the frequency of meshing is in the range of 330 Hz. The Records are made every day for 13 days. The vibration signal from the test has 60160 samples with a sampling frequency of 20 KHz. One of the teeth of a gear wheel was damaged during the experiment.

Given the large number of data (60160 samples), it is difficult to treat them all. So, we must choose a reduced number of data without losing information about the system. For this, we must at least cover a period. We have the rotational frequency 16.67Hz and the sampling frequency f_{sap}=20KHz. To calculate the number of samples covering the period, we divide the rotation period T on the sampling period. So the number of obtained samples will be 1200 samples. We choose a number of 1500 samples.

The temporal representations of the signal emitted by the system for each day are given in Fig .2.

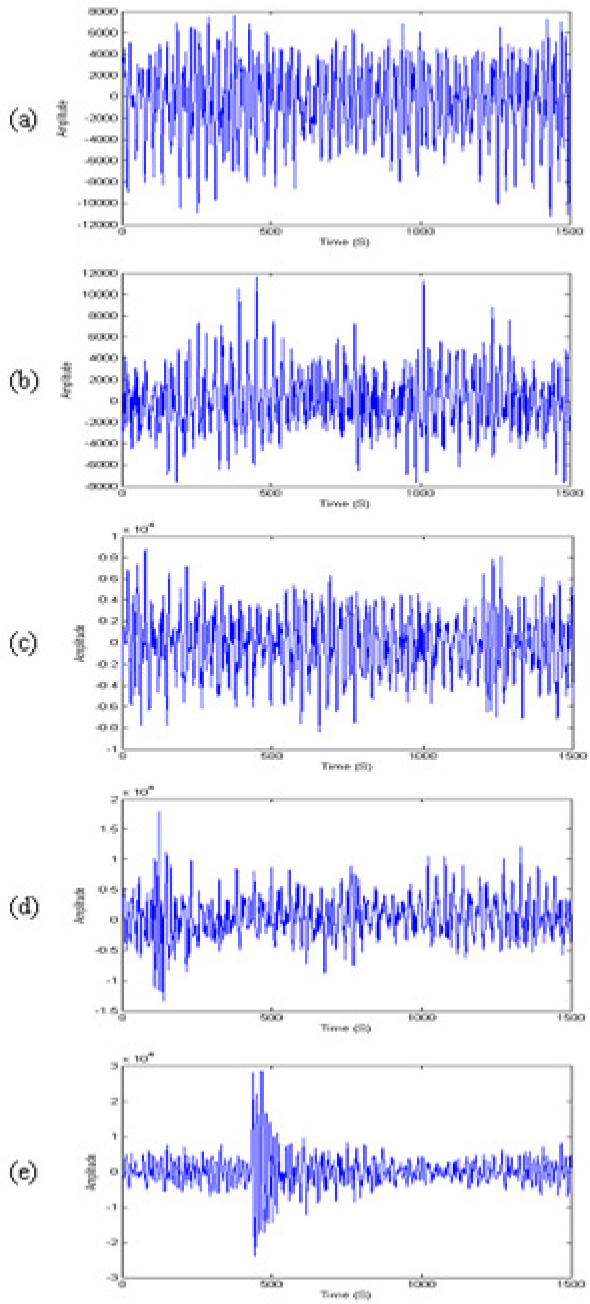

Fig. 2. Vibrations recorded during: (a) 8th day, (b) 9th day, (c) 10th day, (d) 11th day and (e) 12th day. Displaying over 2 periods of rotation relative to the pinion.

We note that the temporal representation of signals observed each day presents oscillations caused by teeth meshing and a modulation of long duration corresponding to the period of the two wheels (pinion of 20 teeth and wheel of 21 teeth). The vibration signal keeps this shape until the 12th day during which the fault is supposed to appear. We observe a very high increase of signal amplitude around modulations relative to oscillations between these last ones. These observations allow the diagnosis of a fault in the 12th and 13th days.

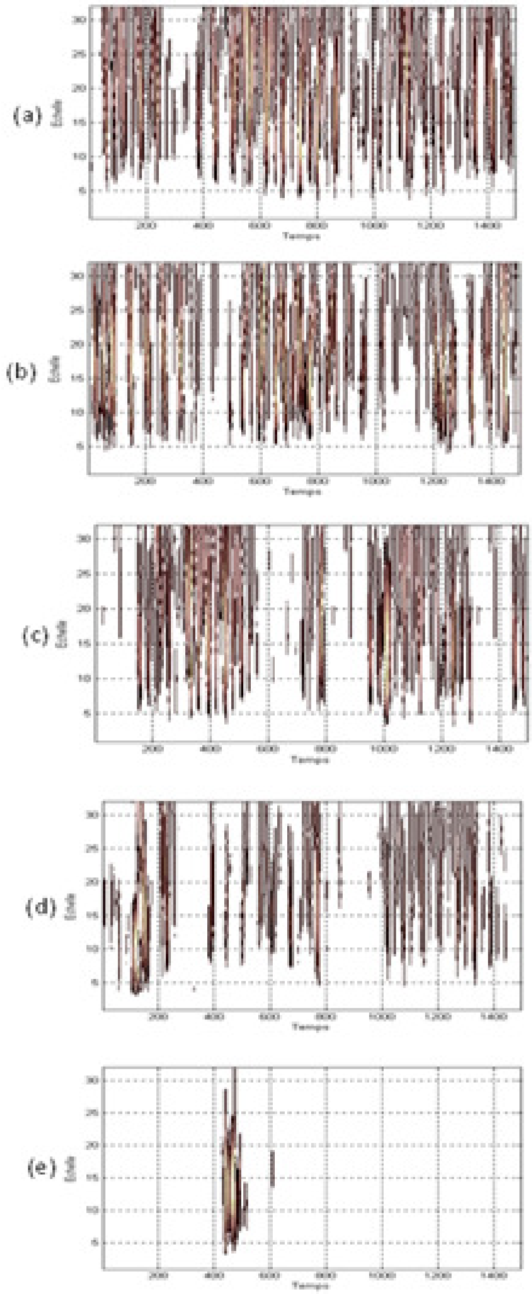

Fig.3. Vibrations recorded during: (a) 8th day, (b) 9th day, (c) 10th day, (d) 11th day and (e) 12th day. Displaying over 2 periods of rotation relative to the pinion.

In the area of wavelet transform (Fig.3), the coefficients are stable and have similar magnitudes until the 9th day.

At the 10th day, the coefficients start changing their behavior. We observe the absence of a part of the band on the scalogram. This is an early indication of the presence of a gear defect. The gear system has a defect on the 12th day corresponding to the tooth damage which results in a complete change in the location of the wavelet transform coefficients.

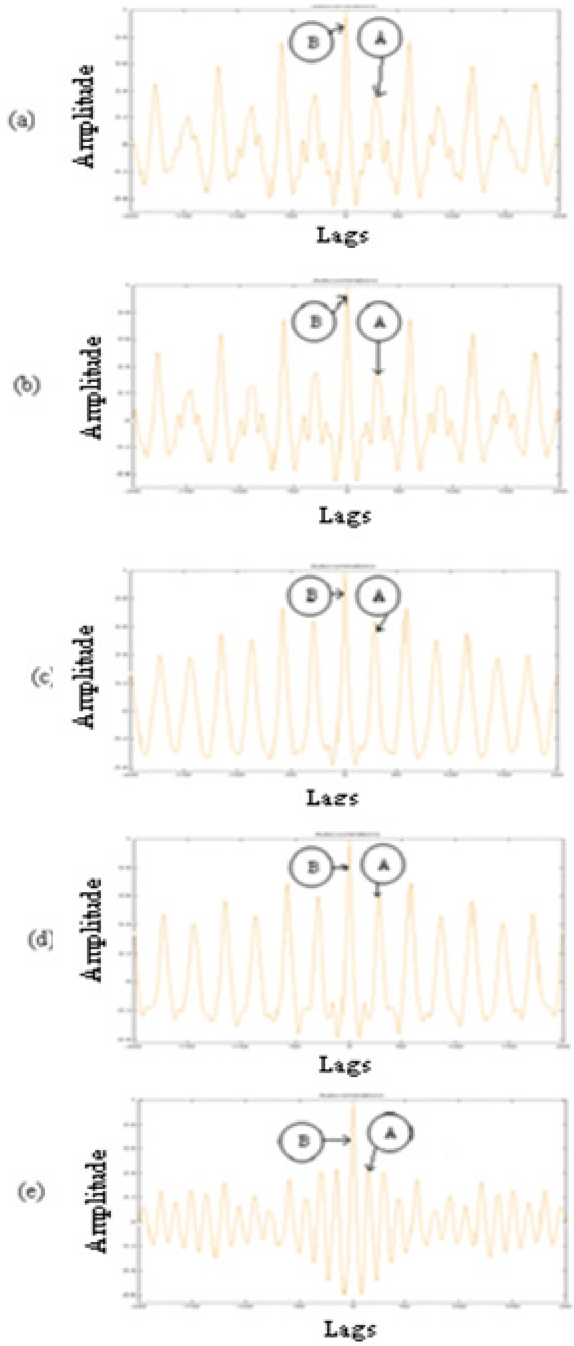

Fig.4. Autocorrelation Vibrations recorded during: (a) 8th day, (b) 9th day, (c) 10th day, (d) 11th day and (e) 12th day.
A: peak of wheel with 21 teeth. B: peak of wheel with 20 teeth.

We observe, according to figure 4, from the 2nd to the 9th day the presence of a relatively weak change in amplitude of peaks of the wheel with 21 teeth and of the pinion with 20 teeth. This change is due to many phenomena such as the level and quality of the lubricant.

At the 10th day, the peaks amplitude of the 21 teeth is increased and this is an early indication of presence of the defect.

At the 12th and 13th day, we observe the appearance of a fault on the pinion in an obvious manner by an increase of the peak characterizing it and by its localization.

IV. Conclusion

Rotating machines play an important role in many industrial applications. Gear is one of the most important and frequently encountered components in rotating machinery and the significant challenge remains with the monitoring of these gears under fluctuating operating conditions.

The aim of this work is the detection of the fault presence in early stage. The application of autocorrelation of optimal wavelet transform to vibration signals showed that the peak amplitude of the 21 wheel teeth increases in the 10th day. This allows the early detection of gear failure before the 12th day (the day of manifestation of a defect) and the fault localization on the wheel with 21 teeth; but we can't observe this early detection in the temporal representation of the vibration signals. The results of a real signal test demonstrate that the proposed method is effective.

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