Early Detection Of Defect In Gear Systems Using Autocorrelation Of Adaptive Morlet Wavelet Transforms

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***Abstract*—The gears are in high demand in the transmission systems of mechanical energy. The role of the gears is to transmit motion or power between two trees at a constant speed ratio. The materials used will vary according to the uses. In this paper, we propose a new method for the fault diagnosis of a gear system made of two toothed wheels operating at constant conditions. This method is based on the autocorrelation of Adaptive Morlet wavelet transforms (AMWM). It is applied on real gear signals for the purpose of early detection of defects present in an experimental tested gear system.**

***Keywords*—Early gear defects detection; Autocorrelation fonction; Adaptive Morlet wavelet transforms (AMWM);**

I. Introduction

Monitoring and gear faults diagnosis are essential to prevent a serious defect in mechanical systems. The information in the monitoring can be used for planning of maintenance activities. Vibration analysis based on signal processing is an effective approach for the analysis, the detection and the gear faults diagnosis. The early detection of defects in mechanical systems is very important for operators and has attracted the attention of many researchers in recent years [1-3]. Their aim is planning the repair of these systems rather than catastrophic damage caused by unexpected defects. There are several techniques in the literature for the early faults detection based on vibration analysis. Vibration analysis uses signal processing tools in the time, frequency and time-frequency domains. Each technique has advantages and limitations. The basic principle of vibration analysis based on the fact that a change in the mechanical systems conditions can induce a change in the vibrations produced by this system. In simple systems, this change may take the form of an increasing in amplitude of the vibration signal. For more complex systems, the change in the vibration signal due to deterioration of a machine organ will be less considerable, and to identify the defect, more sophisticated techniques are required.

The gear reductors are present in all mechanical machines. We find them in most industrial sectors such as the speedbox in automobile industries. Researchers are still very interested in the study of gear reductors because of their relative weakness [2-5].

According to Li [6], Gear system is an essential element widely used in a variety of industrial applications. Since approximately 80% of the breakdowns in transmission machinery are caused by gear failure, the efficiency of early fault detection and accurate fault diagnosis are therefore critical to normal machinery operations. When the localized fault occurs in gears, periodic impulsive characteristics of the vibration signal appears in the time domain, and the corresponding frequency components will emerge in the frequency domain. However, an effective signal processing method is needed to eliminate noise and interference. Su et al, in [7], propose a new method based on Morlet wavelet and autocorrelation. At the beginning, to eliminate frequencies associated with interfering vibrations, the signal is filtered by a band pass filter built by Morlet wavelet.

In this paper, we propose a new method based on the autocorrelation function of Adaptive Morlet wavelet transforms. This method is applied on real gear signals for the purpose of early detection of defects present in an experimental tested gear system.

II. Continuous wavelet transform

The wavelet transform provides a combination of time and frequency localisation, and thus it is important for analyzing non-stationary signals. The proposed method is based on the continuous wavelet transform, so a brief definition of continuous wavelet transform is given.

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

$$\mathrm{CWT} = |a|^{-1/2} \int_{-\infty}^{+\infty} x(t)\Psi^{*}\left(\frac{t-b}{a}\right) dt \qquad (1)$$

The function Ψ is called mother wavelet or basis wavelet [8].

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

The corresponding family of wavelets consists of a series of daughter wavelets, which are generated by dilation and translation operations from the mother wavelet $\Psi(t)$ shown as follows:

$$\Psi_{a,b}(t) = |a|^{-1/2}\, \Psi\left(\frac{t-b}{a}\right) \qquad (2)$$

(a) and (b) are scaling (dilation) and translation parameters, respectively. The scale parameter a will decide the oscillatory frequency and the length of the wavelet, the translation parameter b will decide its shifting position [8-10].

From the mother wavelet, all the functions of the family of wavelets will deduct, the parameter (b) positions the wavelet on the time axis, while the parameter (a) controls the frequency of the wavelet (contraction: high-frequency expansion: low frequency).

If $|a| \ll 1$, the wavelet $\Psi_{a,b}(t)$ is highly concentrated in the mother wavelet $\Psi(t)$ and the frequency content shifted towards the high frequencies of the analysis plan.

If $|a| \gg 1$, the wavelet $\Psi_{a,b}(t)$ is very large and the frequency content focus on the low frequency analysis plan [8-10].

If we vary the parameter of expansion (a), the wavelet keeps the same number of oscillations [8].

The Morlet wavelet is defined as a complex exponential function in the time domain and has a shape of Gaussian window in the frequency domain as follows [4]:

$$\Psi(t) = \exp(j2\pi f_c t) \exp(-t^2/f_b) \quad (3)$$

Where (f_b) is the bandwidth parameter, (f_c) is the central wavelet frequency.

The parameters (f_b) and (f_c) control the shape of the Morlet wavelet and balance the time-frequency resolution. So, there always exists a most favorable pair of parameters (f_b) and (f_c) that has the best time-frequency resolution for a certain signal localized in the time-frequency plane.

In our paper [4], we have proposed a new method based on Adaptive Morlet Wavelet (AMWT) for the analysis of vibration signals produced from a gear system under test in order to early detect the presence of faults. The mother Morlet wavelet is adapted with the gear vibration signal by setting parameters of the wavelet to balance the time-frequency resolution. The obtained optimal pair of parameters results in the best time-frequency resolution for the given vibration signal.

III. AUTOCORRELATION COEFFICIENTS

Random vibrations are by nature unpredictable, so the future values of the signal can be defined only on the basis of probabilities. We consider the random signal as the stochastic process realization, i.e the time evolution of a random variable. We speak about cyclostationnarity of a stochastic process representing the signal when the statistical parameters that govern vary periodically. The autocorrelation function calculates the internal dependencies of the signal. For example, in the case of sinusoidal signal, the autocorrelation coefficients are highly uniform and homogeneous; so, the signal will have a strong autocorrelation.

The rotating machines vibration signals consist of periodic and random components. The autocorrelation function is suggested to detect the periodicity of the default signature [11]. The autocorrelation can better understand the evolution of the process through time by using the probability of the relationship between the data values separated by a specific number of time steps called “lags” [7, 11-12].

For a signal $s(t)$, the autocorrelation function $R_x(t)$ is generally defined as the cross-correlation of the signal $s(t)$ with itself. The cross-correlation of a signal $x(t)$ and $y(t)$ is given by the expression [5, 7, 11-12]:

$$R_{xy}(t) = \sum_{n=0}^{\infty} x(n)y(n+r) \quad (4)$$

If $x(n) = y(n)$, the equation (1) becomes an autocorrelation function:

$$R_x(t) = E[x(t), x(t-\tau)] \quad (5)$$

Where: (τ) is the specific time step (lag).

$E[,]$ is the mathematical esperance operation.

For ergodic process, esperance can be replaced by the limit of the time average. The autocorrelation of an ergodic process is defined by:

$$R_x(t) = \lim_{T\to\infty} \int_0^T x(t).x(t+\tau)dt \quad (6)$$

The autocorrelation function reaches its peak in the beginning; where it takes the real value, i.e:

$$|R_x(\tau)| \le |R_x(0)| \quad (7)$$

The autocorrelation function of the wavelet coefficients is defined as the integral of the product of the wavelet transform $TO_{a,b}(t)$ with itself delayed by (τ) according to the following equation:

$$R_{xx}(t) = \int_{-\infty}^{+\infty} TO_{a,b}(t) \times TO_{a,b}(t+\tau)dt \quad (8)$$

We call the center point where the autocorrelation reaches its maximum a peak point OPM (Origin Point Maximum). If the size of a function $x(t)$ is equal to (M) where: (M> 1), the autocorrelation function has a dimension of $(2 \times M - 1)$.

The proposed method for predicting defects of rotating machines consists to calculate the autocorrelation of the wavelet transform of the Adaptive Morlet Wavelet (AMWT). In this case, the AMW is a two-dimensional matrix $(M \times N)$, and in consequence the autocorrelation function will also be two dimensional $(O \times P)$ with: $O = 2 \times M - 1$ and $P = 2 \times N - 1$.

IV. DESCRIPTION OF THE SYSTEM UNDER STUDY

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) [4-5, 13-14]. 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. The expertise report is given in table 1 [15]:

TABLE I. THE EXPERTISE REPORT [CHIKOUCHE, 2010].

Day	Observations
1	1st day of acquisition, no anomaly
2	No anomaly
3	// //
4	// //
5	// //
6	Crack of tooth 1/2
7	No evolution
8	Tooth 1/2 no evolution, tooth 15/16 start of crack
9	Evolution of crack tooth 15/16
10	// //
11	// //
12	Crack in all width of the tooth 15/16

V. RESULTS AND DISCUSSIONS

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 fsap =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 [4].

A. Temporal representations of the signal and scalograms

The temporal representations of the signal emitted by the system for each day are given in Fig. 1. We have given the temporal representation of the days: 8, 9, 10, 11 and 12. i.e two days before the appearance of the defect and two days after, in view of that we arrive to detect the defect in the 10^{th} day [4].

The temporal representation of the vibratory gear signal during the first eleven days doesn't give further indication characterizing the occurrence of a fault. From Fig. 1, it can be seen that the temporal representation of the 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 vibratory signal keeps this shape until the 11th day. As against the 12^{th} day, during which the default is assumed to occur in the form of crack in the full width of the 15/16 tooth according to the expert report (Table 1), shows a different representation. We observe a very high increase of the signal amplitude around modulations relative to oscillations between these last ones. So the temporal representation permits to diagnose a fault in the 12^{th} day.

In the scalograms domain, we see from Fig. 2 that the coefficients are stable and has the same order of magnitude until the 9th day with a relatively small amplitude change in the coefficients. This change is due to a number of phenomena, such as the level and the quality of the lubricant for example. This change is also due, according to the expert report (Table 1), to crack of the tooth 1/2 in the 6th day, start of crack in 15/16 tooth in 8^{th} day and evolution of crack in 15/16 tooth (the expert report).

At the 10^{th} day, we observe the complete disappearance of part of the AMWT coefficients. This disappearance of the coefficients is an early sign that indicates that the gear system will suffer faults and this is due to the evolution of the crack in the 15/16 tooth. The gear system has a defect (peeling over the entire width of tooth 15/16) in the 12^{th} day which translates into a complete change of the location of the AMW coefficients.

The aim of this part consist to determine the AMWT of the vibratory signal delivered from the gear system and accurately follow the evolution of the coefficients obtained during the days of operation of the system in the purpose of the early detection and location of a fault before the spreading of the crack over the entire width of the tooth.

In addition to its simple implementation, the technique of AMWT presents a very effective tool in the early diagnosis of gear reducer's faults in rotating machinery. It can diagnose a fault at the 10th day (2 days before the full onset of the fault).

B. Obtained results from the autocorrelation of the AMWT

In this section, we apply the method of the autocorrelation function on scalograms obtained by applying the AMW on vibratory signal issued from the CETIM gearbox. The results obtained are given in Figures 3 and 4.

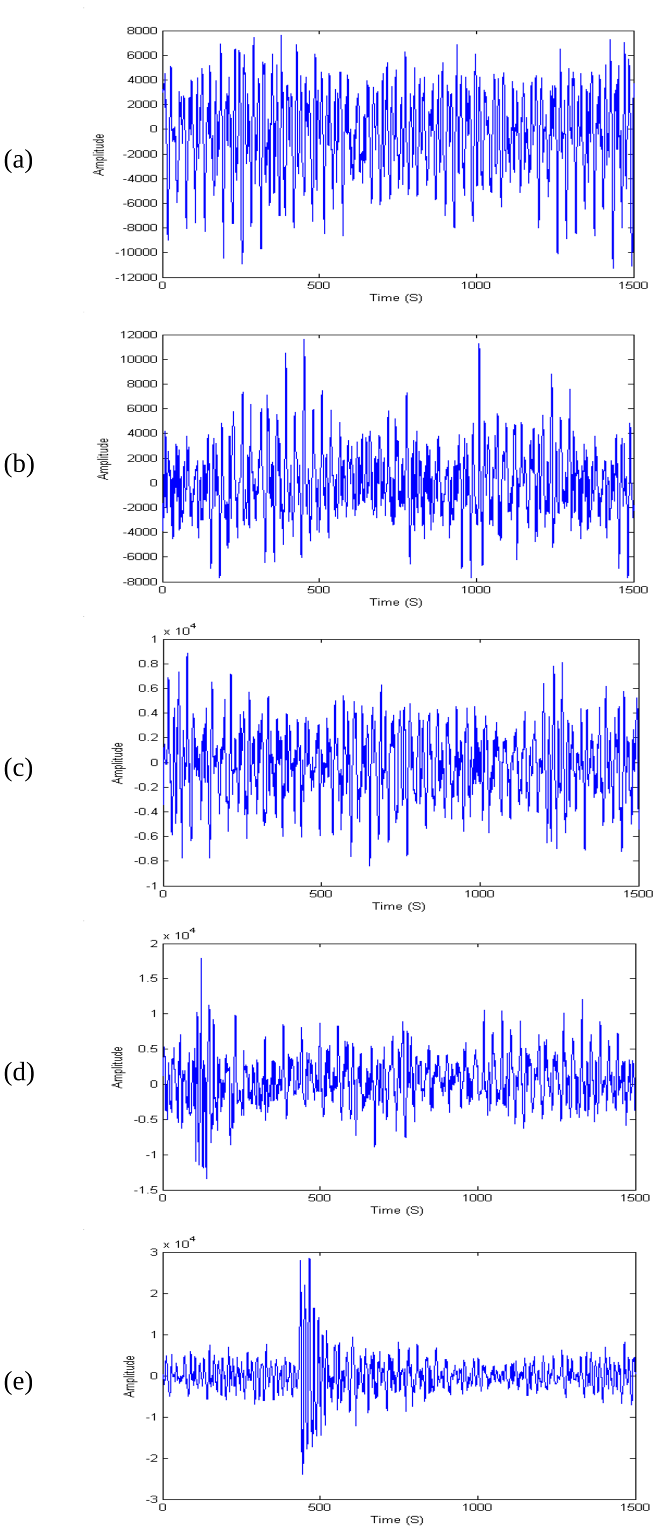

Fig.1 CETIM gear vibration signals recorded during: (a) 8th day, (b) 9th day, (c) 10th day, (d) 11th day and (e) 12th day. Displaying over 2 periods of rotation relative to the pinion. [4]

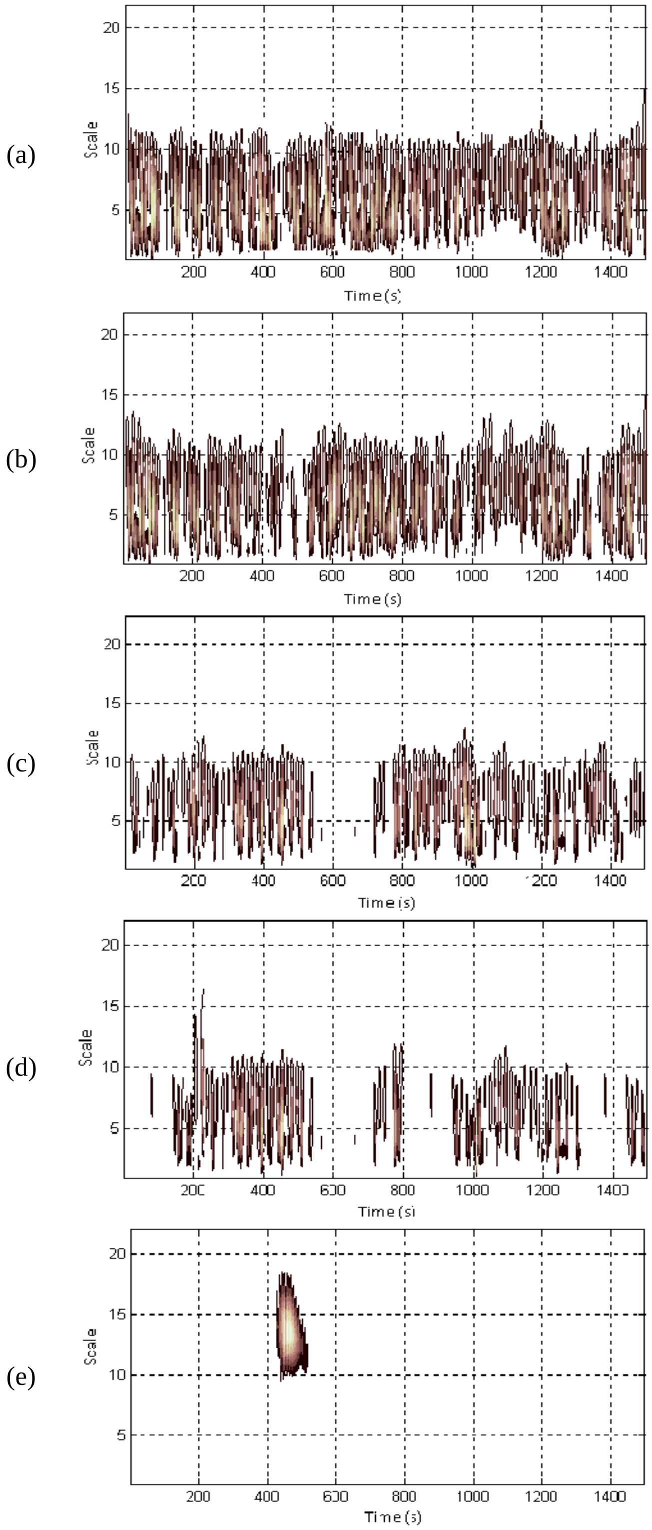

Fig .2 AMW scalograms of CETIM gear vibration signals using the maximum Morlet wavelet coefficients as a cost function: (a) 8th day, (b) 9th day, (c) 10th day, (d) 11th day and (e) 12th day [4]

(a) (b) (c) (d) (e)

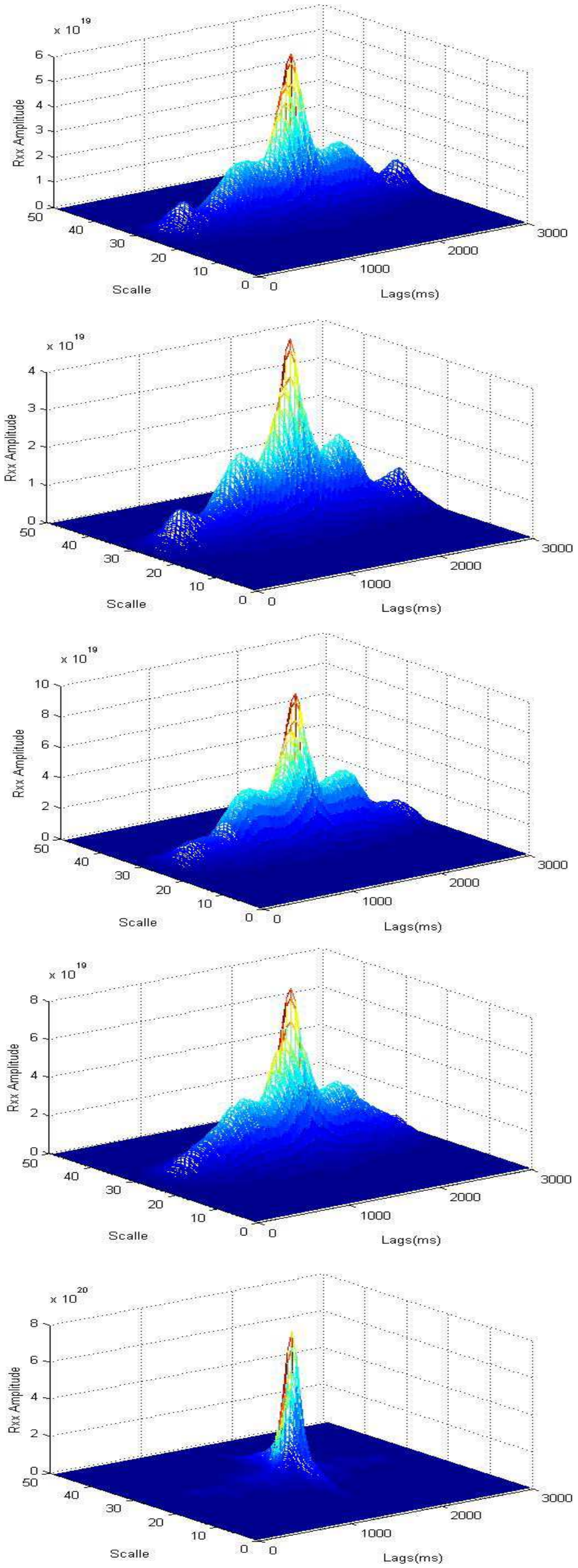

Fig.3: AMWT autocorrelation of CETIM gear vibration signals recorded during:
(a) 8th day, (b) 9th day
(c) 10th day, (d) 11th day and (e) 12th day

(a') (b') (c') (d') (e')

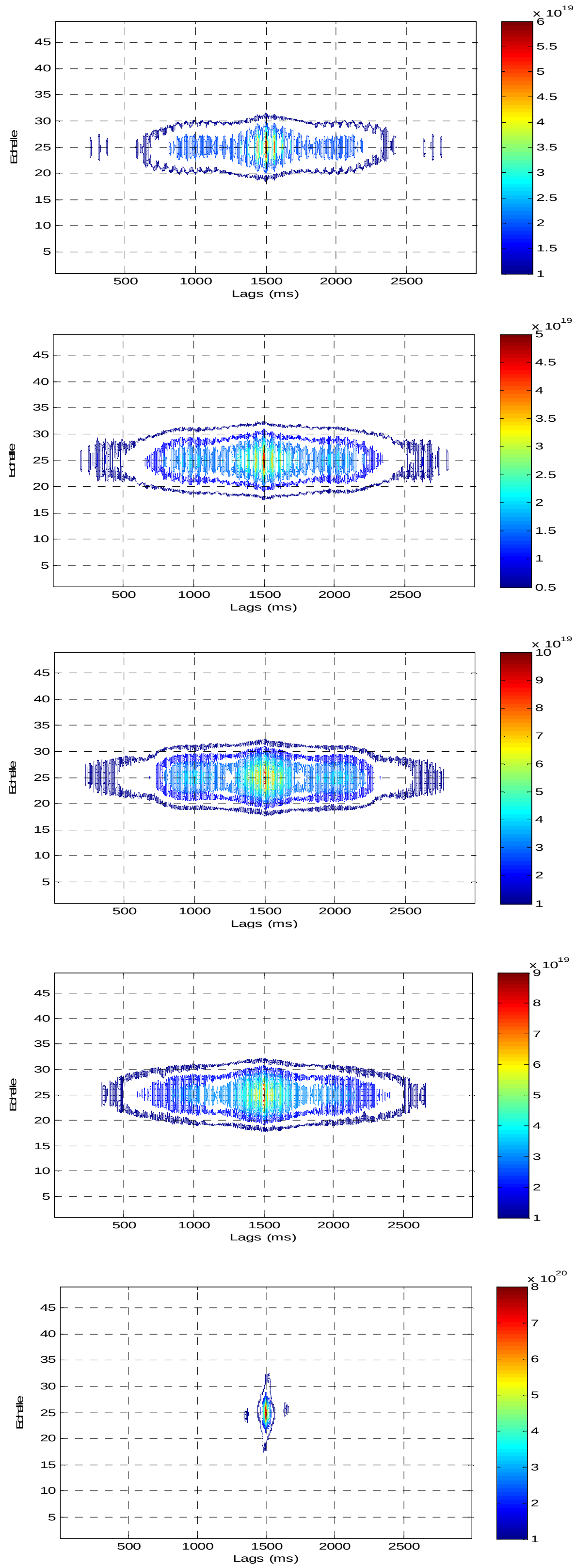

Fig.4: Contour of AMWT autocorrelation of CETIM gear vibration signals recorded during:
(a) 8th day, (b) 9th day
(c) 10th day, (d) 11th day and (e) 12th day

From Figure 3 and Figure 4, we observe that the autocorrelation functions of the AMWT, are similar and have the same order of magnitude until the 9th day with an OPM peak amplitude of $\mathrm{OPM}(1500,25) \approx 6 \times 10^{19}$ (Table 2). These small variations are due to several phenomena and causes mentioned in the expertise report (Table 1).

At the 10^{th} day, an increase of the autocorrelation function is observed with an OPM peak amplitude of value $\mathrm{OPM}(1500,25) = 10.04842673892965 \times 10^{19}$. This increase is the early sign of the presence of a fault in the gear system. This defect is due to the evolution of the peeling in the 15/16 tooth (the expertise report).

At the 12^{th} day and with the crack over the entire width of tooth 15/16, the autocorrelation function becomes very large (the OPM peak amplitude reaches the value of $\mathrm{OPM}(1500,25) = 80.54631341778420 \times 10^{19}$).So the autocorrelation function applied to the AMWT scalograms can detect the presence of a fault at an early day, i.e. the 10th day (2 days before the full appearance of the fault).

Finally, we can say that the autocorrelation function of the AMWT presents a very effective tool in the early diagnosis of gear reducer's faults in rotating machinery.

The OPM peak amplitude values of all days are given in table 2 below:

TABLE II. THE OPM PEAK AMPLITUDE VALUES.

The days	OPM peak amplitude
5^{th} day	$(1500{,}25) = 6.626733030945805 \times 10^{19}$
6^{th} day	$(1500{,}25) = 6.090234832595839 \times 10^{19}$
7^{th} day	$(1500{,}25) = 6.586669410632360 \times 10^{19}$
8^{th} day	$(1500{,}25) = 6.437468137514745 \times 10^{19}$
9^{th} day	$(1500{,}25) = 5.090191841432165 \times 10^{19}$
10^{th} day	$(1500{,}25) = 10.04842673892965 \times 10^{19}$
11^{th} day	$(1500{,}25) = 9.084636336550063 \times 10^{19}$
12^{th} day	$(1500{,}25) = 80.54631341778420 \times 10^{19}$

VI. CONCLUSION

In this paper, a gear box diagnosis technique based on the autocorrelation of Adaptive Morlet wavelet transforms. The performances of this technique in the gear system diagnosis have been discussed. The application of this technique to the vibration signal emitted by the gear reductor system permits to conclude that it can play an important role in the study of gear vibrations. In fact, the use state of a reductor is strongly related to modulation phenomena that present the vibrations relative to the meshing signal. We have shown that vibration analysis through the autocorrelation based technique permits to detect the fault presence and determine the deteriorated wheel at the 10th day. Consequently, this technique is very efficient for the diagnosis of faults in gear reductors.

Finally, we can say that in addition to its simple implementation, the technique of autocorrelation of Adaptive Morlet wavelet transforms has a very effective and valuable tool in the early diagnosis of gear reducer's faults in rotating machinery.

REFERENCES

[1] W. D. Mark, H. Lee, R. Patrick, J. D. Coker, "A simple frequency-domain algorithm for early detection of damaged gear teeth," Mechanical Systems and Signal Processing, Vol. 24, pp. 2807–2823, 2010

[2] C.Y. Yang, T.Y. Wu, "Diagnostics of gear deterioration using EEMD approach and PCA process," Measurement, Vol. 61, pp.75–87, 2015.

[3] T. Sipola, T. Ristaniemi, A. Averbuch, "Gear classification and fault detection using a diffusion map frame work, Pattern Recognition Letters," Vol. 53, pp.53–61, 2014

[4] M. Ayad, Dj. Chikouche, N. Boukezzoula, M. Rezki, "Search of a robust defect signature in gear systems across adaptive Morlet wavelet of vibration signals," IET Signal Processing, Vol. 8 (Issue N° 9), p. 918 – 926, 2014.

[5] M. Ayad, Dj. Chikouche, N. Boukezzoula, M. Rezki, "Gear Fault Diagnosis Across Autocorrelation of Optimal Wavelet Transforms," Special issue - International Conference on Control, Engineering & Information Technology (CEIT'14) Proceedings -Copyright IPCO-2014, Vol. 6, pp. 17-21, 2014.

[6] Z. Li, X.Yan, C. Yuan, Z. Peng, L. Li, "Virtual prototype and experimental research on gear multi-fault diagnosis using wavelet-autoregressive model and principal component analysis method," Mechanical Systems and Signal Processing, 25, pp. 2589–2607, 2011.

[7] W. Su, F. Wang, H. Zhu, Z. Zhang, Z. Guo, "Rolling element bearing faults diagnosis based on optimal Morlet wavelet filter and autocorrelation enhancement," Mechanical Systems and Signal Processing, 24, pp. 1458–1472, 2010.

[8] I. Daubechies, "The wavelet Transform, Time-frequency Localisation and Analysis," IEEE, transactions on information theory, 1990, 36, pp. 961–1004

[9] S. Mallat, 'A theory for multiresolution signal decomposition: the wavelet representation', IEEE Pattern Analysis and Machine Intelligence., 1989, 11, (7), pp. 674–693

[10] H. Olkkonen, J. T. Olkkonen, "Shift-invariant B-spline wavelet transform for multi-scale analysis of neuroelectric signals," IET, Signal Processing, 2010, 4, (6), pp. 603–609

[11] J. Rafiee, P.W.Tse, "Use of autocorrelation of wavelet coefficients for fault diagnosis," Mechanical Systems and Signal Processing, Vol. 23, pp. 1554–1572, 2009.

[12] P.K. Kankar, S. C. Sharma, S.P. Harsha, "Fault diagnosis of rolling element bearing using cyclic autocorrelation and wavelet transform", Neurocomputing, Vol. 110, pp. 9–17, 2013.

[13] J. Antonia, R. B. Randall, "The spectral kurtosis: application to the vibratory surveillance and diagnostics of rotating machines," Mechanical Systems and Signal Processing, Vol. 20, pp. 308–331, 2006.

[14] A. Parey, M. El-Badaoui, F. Guillet, N. Tandon, "Dynamic modelling of spur gear pair and application of empirical mode decomposition-based statistical analysis for early detection of localized tooth defect," Journal of Sound and Vibration, Vol. 294, pp. 547–561, 2006.

[15] Dj. Chikouche, A. Felkaoui, N. Haloui, "Diagnostic precoce d'un reducteur a engrenage par analyse des signaux vibratoires a l'aide du cepstre synchrone," Proceding International Conference On Industrial Engineering and Manufacturing ICIEM'10, May, 9-10, Batna, Algeria, pp. 219-224, 2010.