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Search of a robust defect signature in gear systems across adaptive Morlet wavelet of vibration signals

Mouloud Ayad[1,4], Djamel Chikouche[2,4], Nacereddine Boukazzoula[1,4], Mohamed Rezki[3]

[1]*Department of Electronic, Faculty of Technology, Setif-1 University, Algeria*
[2]*Department of Electronic, Faculty of Technology, M'sila University, Algeria*
[3]*Department of Electronic, Faculty of Applied Technology, Bouira University, Algeria*
[4]*LIS Laboratory, Setif-1 University, Algeria*
E-mail: ayad_moul@yahoo.fr

Abstract: Monitoring of rotating machines by vibration analysis is a topic that has received a great interest in recent years. Moreover, the vibrations from a machine are affected greatly by the conditions of its operation (speed, load and so on). A significant challenge remains with the monitoring of gears under fluctuating operating conditions. An unexpected fault of gear may cause huge economic losses, even personal injury. In this study, a new method based on adaptive Morlet wavelet (AMW) is proposed for the analysis of vibration signals produced from a gear system under test in order to detect early 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; and the fault detection problem is considered just as a simple signature search in the time-scale domain using scalograms. An early indication of the presence of a gear defect is obtained at the 10th day of experimentation using the AMW-based method. Whereas, 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 AMW coefficients.

1 Introduction

Monitoring of rotating machines by vibration analysis is a topic which has received a great interest in recent years. Initially, it was destined to make the installation safe and to avoid significant degradation directly by triggering its decision when the values of vibration amplitude are considered excessive. This monitoring becomes the foundation of a new maintenance strategy: the predictive maintenance. Knowledge of machines and their behaviour is not more funded by the memory of the operators. It is not more than the sense of individuals who used to understand the drift and evaluate the state of installation, but supervision systems and materials are themselves poorly monitored. The tools of the conditioned maintenance will allow better appreciation of the 'health' of machines and systems: vibration analysis, deformation, heat flow, noise and so on. Sensors, measurement systems and data processing provide valuable information on trends and evolution in the behaviour of some organs. Condition of monitoring tools facilitates also the rationalisation act of diagnosis [1].

To diagnose early fault of rotating machines, feature extraction of vibration signals is a very important and difficult research task in engineering. The vibration signal of rotating machines is usually non-stationary, non-linear and with strong noise interference. Meantime, the early signal energy is too low to extract fault features in the time domain [2]. Signal processing is an approach widely used in diagnostics, since it directly allows characterising the state of the system. Several types of advanced signal processing techniques have been proposed in the last decades and added to more conventional ones [1–28]. Since each technique has different theoretical basis, the obtained results are also usually different. Some techniques may be more suitable than others for a specific system or component, depending on the environmental conditions. Therefore, it is important to choose techniques that are most effective for the case and the situation under testing for a reliable diagnosis [3, 4].

Rotating machines like the compressor, steam turbine, automotive, industrial fan and aircraft engine are widely used in many industrial fields. How to extract the fault features and identify the condition from the vibration signals are the key steps in the fault diagnosis of rotating machines [3–5]. As the fault vibration signals of rotating machines are usually non-stationary, it is difficult to obtain feature vectors from them for the fault diagnosis. The traditional diagnosis techniques perform this from the waveforms of the fault vibration signals in the time or frequency domain, and then construct the criterion functions to identify the working condition of a rotating machine. However, because the non-linear factors (loads, clearance, friction, stiffness and so on) have distinct influence on the vibration signals because of the complexity of the constructing and working condition of rotating machines, it is difficult to make an accurate diagnosis on the working condition of rotating machines only through the analysis in time or frequency domain [6].

The gear transmissions 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 transmissions because of their relative weakness [29–41]. Signal analysis is considered as one of the important means used for gear fault diagnostics. The important information and the dominant features contained in the signals can be extracted in order to detect faults in gear systems. The FFT-based methods have been widely used for fault diagnostics but they are not suitable for non-stationary signal analysis. Since the vibration signals delivered from gears contain non-stationary components because of gear faults, we must find robust signal processing methods [1–28] to analyse the non-stationary vibration signal. We can use time–frequency transforms, such as the Wigner–Ville distribution [42] and the short time Fourier transform (STFT) [43] to analyse vibration signals. However, these techniques provide a constant resolution for all frequencies because of the same window used for the analysis of the entire signal. In order to overcome these disadvantages, the continuous wavelet transform (CWT) has been introduced by Morlet in 1984. In 1985, Meyer established an interesting orthogonal wavelet base with very good time and frequency localisation properties. In the following year, Meyer and Mallat introduced the multi-resolution analysis that led to the famous fast wavelet transform [41]. The paper [44] published by Daubechies has made wavelets more popular.

Because of the multi-scale analysis of a signal by dilation and translation, the wavelet transform can extract time–frequency features of a signal more effectively than the STFTs. That is why the wavelets have been successfully used in gear fault diagnostics [41]. The gear vibration signals have been analysed with wavelets, by Wang and McFadden [29] in 1993, in order to detect different types of faults simultaneously through representing the different scale of features in the vibration signal in a single three-dimensional display. The research work done by Newland in 1999 made the wavelets popular in the vibration signal analysis in particular and in engineering applications in general.

The square of the CWT modulus, known as scalogram, has been used by Boulahbel *et al.* [45] on the residual vibration signal of gears to detect the precise location of a tooth defect. Several applications of scalogram have been published in the domain of tooth defects detection in gear systems [46–49] in which the authors have shown that the propagating crack led to changes in vibration amplitudes with the frequencies corresponding to the rotation frequency harmonics [41, 50]. Further research has been carried out on the use of phase spectrum and coefficient thresholding of the wavelet to detect the signal discontinuities [45, 48] in gear systems. Even though the wavelet is capable to perform better than the FFT and STFT, it still has some disadvantages, such as the effects of border distortion, the energy leakage and the great sensitivity of its phase spectrum with noise [51–53].

The detection of the early fatigue cracks in gears has been performed by Hambala and Huff [54] using discrete wavelet transform to decompose the vibration signals from gears. The wavelet transformed signals are then approximated at each level and the probability density functions (PDFs) of the residual errors are expanded into Hermite polynomial. The coefficients of this expansion are used to early detect the fatigue cracks in gears. Wang and McFadden have applied an orthogonal wavelet transform to detect abnormal transients generated by early damage from a gearbox vibration signal [55]. Orthogonal wavelets, such as Daubechies 4, were used to transform the time domain synchronous vibration signal into the time-scale domain. Hence, the wavelet transform permits to determine wavelet coefficients that highlight the changes in vibration signals predicating the occurrence of the fault; which makes possible the early fault detection.

In this paper, an adaptive Morlet wavelet (AMW) is applied to the analysis of vibration signals produced from a gear transmission system under test in order to early detect the presence of faults. Hence, a procedure is proposed in this work, in order to adapt the mother Morlet wavelet with the gear vibration signal by setting parameters of the wavelet to balance the time–frequency resolution. The output of this procedure is an optimal pair of parameters that results in the best time–frequency resolution for the given gear vibration signal. The translation invariance of the AMW allows the definition of a rupture signature. Hence, the fault detection problem will be considered just as a simple signature search in the time-scale domain using scalograms.

The rest of this paper is organised as follows: first, the theoretical background of AMW in Section 2. The simulated signals are applied to evaluate the effectiveness of the method in Section 3. In Section 4, the proposed method is applied in order to early detect the fault of real gear systems. Finally, in Section 5, we give a general conclusion.

2 Theoretical background

2.1 Continuous wavelet transform

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

The CWT of signal $x(t)$ is defined as

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

The function Ψ is called mother wavelet or basis wavelet [6] and (*) 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 the 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 [6–8].

From the mother wavelet, all the functions of the family of wavelets will deduct, the parameter (b) positions the wavelet on the time axis, whereas 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 $|a| \ll 1$, the wavelet $\Psi_{a,b}(t)$ is very large and the frequency content focus on the low frequency analysis plan [6–8].

If we vary the parameter of expansion (a), the wavelet keeps the same number of oscillations [6].

2.2 Adaptive Morlet wavelet

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 most indispensable challenge is the selection of the mother wavelet function as well as the decomposition level of signal. Thus, to find a proper wavelet function for a specific signal is very important.

In this paper, Morlet wavelet is used, because periodical impulses which are always the symptoms of faults will occur when there exists a fault in the Gear system; and Morlet wavelet is very similar to those impulsive components with any signature defect.

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

$$\Psi(t) = \exp\left(\mathrm{j}2\pi f_c t\right)\exp\left(-t^2/f_b\right) \tag{3}$$

where f_b is the bandwidth parameter and 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 (Fig. 1). Hence, there always exists a most favourable pair of parameters f_b and f_c that has the best time–frequency resolution for a certain signal localised in the time–frequency plane.

From Fig. 1 we can observe that the shape of Morlet wavelet depends on both parameters (f_b) and (f_c); where f_b controls the oscillation attenuation of the Morlet wavelet and f_c controls the oscillatory frequency of the Morlet wavelet.

The Morlet wavelet transform is a linear representation, which sums all time the signal $x(t)$ multiplied by scaled, shifted versions of the mother wavelet $\Psi(t)$ in the form [6, 9, 10]

$$W_x(m, n) = 2^{-m/2}\int_{-\infty}^{+\infty} x(t)\Psi^*\left(2^{-m}t - n\right)\,\mathrm{d}t \tag{4}$$

with $m \in \mathbb{R}$; $n \in \mathbb{R} - \{0\}$.

To find the optimal pair of parameters f_b and f_c, we must use the following adaptation procedure:

(1) Choose an initial bandwidth range ($f_b \in [b_1, b_2]$) and a central frequency range ($f_c \in [c_1, c_2]$).
(2) Choose an initial value for the bandwidth step (b) and the central frequency step (c).
(3) Fix the bandwidth parameters f_b to an initial value equal to the lower bound of the bandwidth range f_b, ($f_b = b_1$).

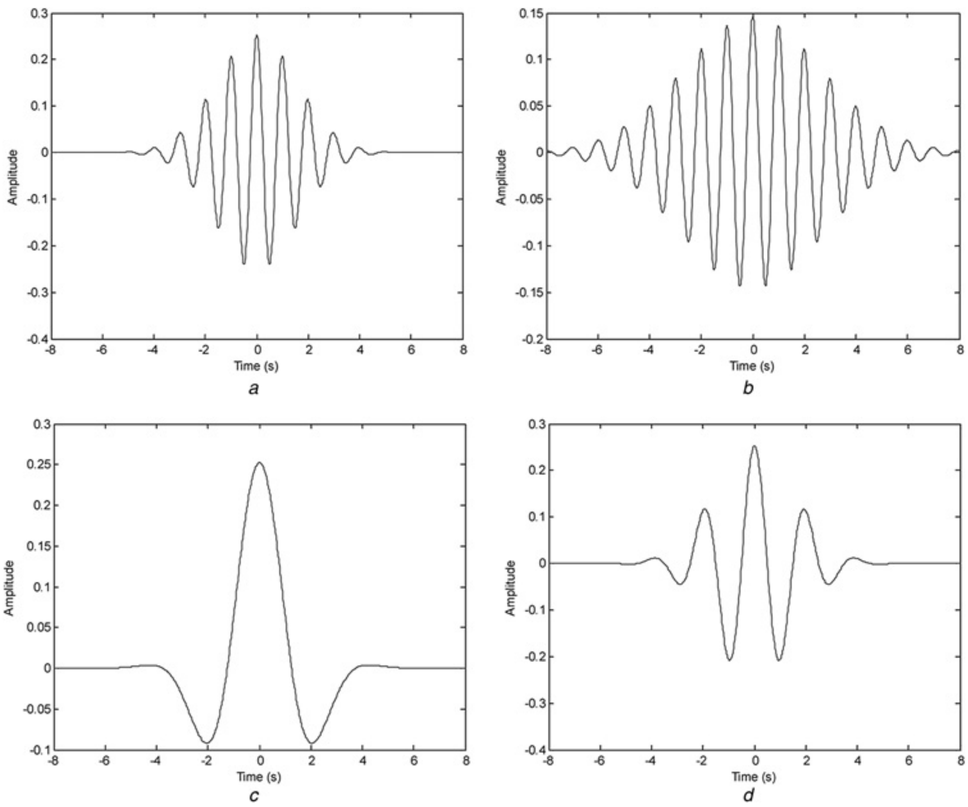

Fig. 1 *The shapes of Morlet wavelet with different (f_b) and (f_c)*

a $f_b = 5, f_c = 1$
b $f_b = 15, f_c = 1$
c $f_b = 5, f_c = 0.2$
d $f_b = 5, f_c = 0.5$

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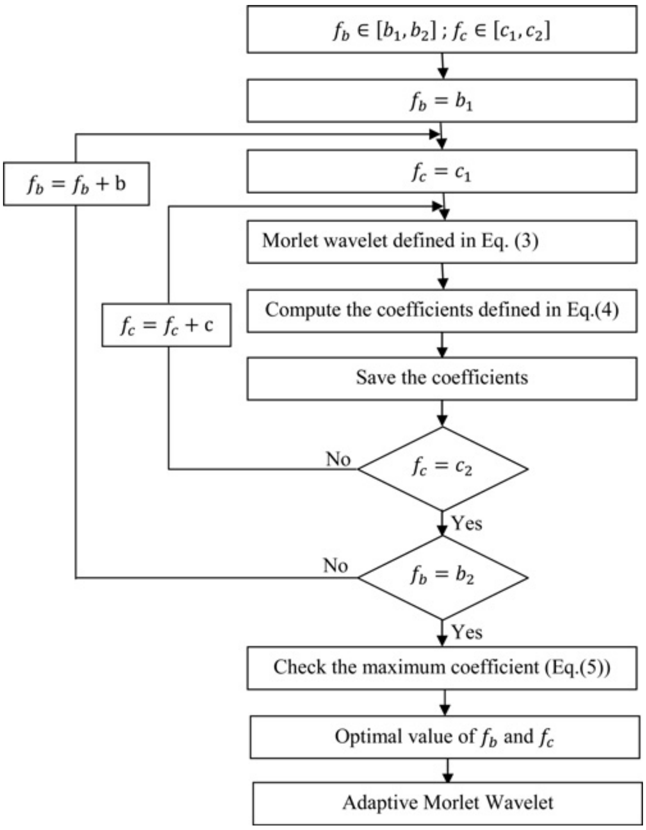

Fig. 2 *The adaptation procedure of the AMW*

(4) For the whole values of f_b, we determine the Morlet wavelet defined in (3) then we compute the Morlet wavelet transform coefficients ($W_x(m, n)$) defined in (4).
(5) Save the $W_x(m, n)$ coefficients for each pair of parameters f_b and f_c.
(6) Check for the maximum values of the coefficient to locate the optimal pair of the parameters f_b and f_c

$$W_{\max} = \mathrm{Max}\left[W_x(m, n)\right] \tag{5}$$

where $W_{\max}$ is the maximum values of the Morlet wavelet coefficients $W_x(m, n)$ and (Max[]) stands for taking the maximum.
(7) Finally, an AMW (Fig. 2) is obtained.

3 Simulation analysis

This section illustrates the validity and the test of the proposed AMW method on a simulated signal for detecting a defect signature. These defects are separated by time intervals where the statistical moments are constant or slightly variable. The location of these defects may be necessary for the segmentation and contour extraction of objects. The AMW is applied firstly to the detection of defects in a multiplicative noise process. Secondly, this work is done to test the performance of the AMW in order to early detect the presence of defects in a real gear system. The property of translation invariance of the AMW permits the definition of a rupture signature [11]. Hence, the detection problem is considered as a simple signature search in time-scale domain using scalograms. Defect detection is a critical application in signal analysis. Defects are separated by a time interval where the moments are constant or variate slightly.

The detection of defects requires specific algorithms [12]. In addition, these algorithms are not always effective in all cases of defects. In our case, the AMW is applied to detect the defect from a signal in the presence of a multiplicative noise. The observation process $y(t)$ is considered as the product of a deterministic signal $s(t)$ with a noise $b(t)$

$$Y(t) = b(t)s(t) \tag{6}$$

where $s(t)$ is a determinist signal and $y(t)$ is a Gaussian white noise.

3.1 Test 1: defect localised at $t = 450$ s

The application of the AMW is performed on a process obtained by the product of a sinusoidal signal having a defect with a Gaussian white noise. Fig. 3 represents this simulated process and its AMW. We note that the defect signature in the AMW coefficients domain (scalogram) is localised at $t = 450$ s, so the defect is located at this time.

3.2 Test 2: Defect localised at $t = 100$ s

Fig. 4 illustrates the results obtained in the case of a defect located at $t = 100$ s. In this case also the AMW is able to detect the defect at $t = 100$ s. However, the AMW remains the most powerful to observe clearly the rupture signature.

In Figs. 3 and 4, the optimal parameters values are $f_b = 5$, $f_i = 1$.

4 Experiments on a real gear system

The effectiveness of the proposed technique is further investigated by using the gear fault vibration signal. The role of gearing is to transmit movement or power between two trees with a constant speed ratio. The used materials vary according to the use, but the most commonly used materials are steel and cast melting. However, plastic materials are increasingly used to transmit a low power.

4.1 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) [13, 14]. They are delivered from a reductor operating 24 h over 24 h. 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 24 h/24 h.

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 meshing signal is periodic; its frequency is equal to the rotation frequency of the one wheel multiplied by the number of teeth of this wheel as below

$$f_e = Z_1 f_1 = Z_2 f_2 \tag{7}$$

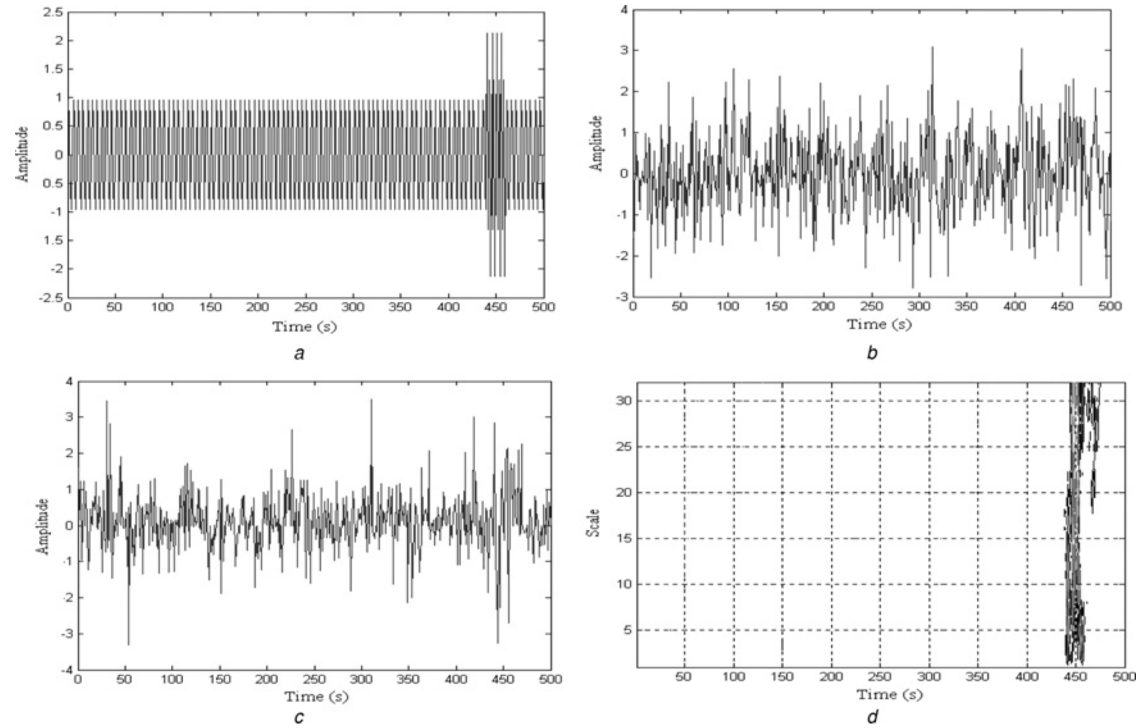

Fig. 3 *Simulated signal for a defect localised at t = 450 s*

a Signal $s(t)$ with a defect at $t = 450$ s
b Gaussian white noise $b(t)$
c Observed process $y(t)$
d AMW scalogram of $y(t)$

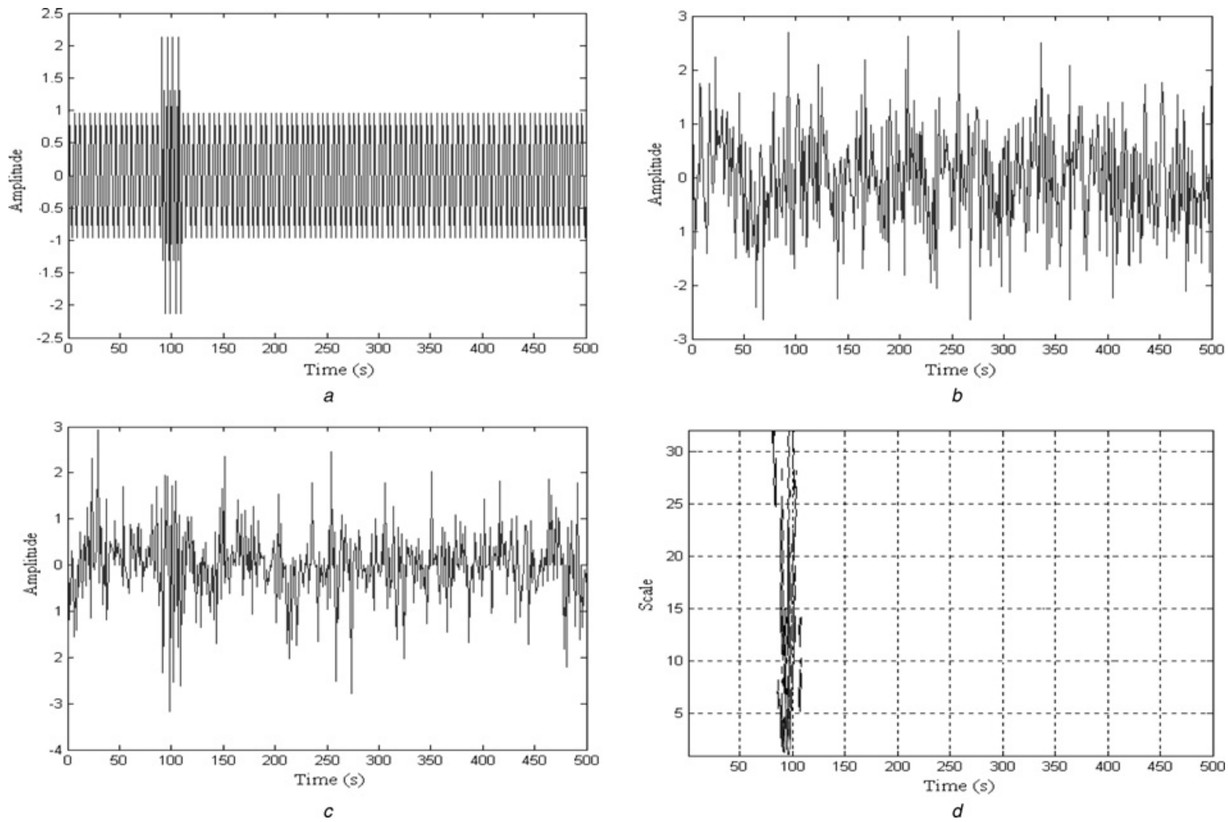

Fig. 4 *Simulated signal for a defect localised at t = 100 s*

a Signal $s(t)$ with a defect at $t = 100$ s
b Gaussian white noise $b(t)$
c Observed process $y(t)$
d AMW scalogram of $y(t)$

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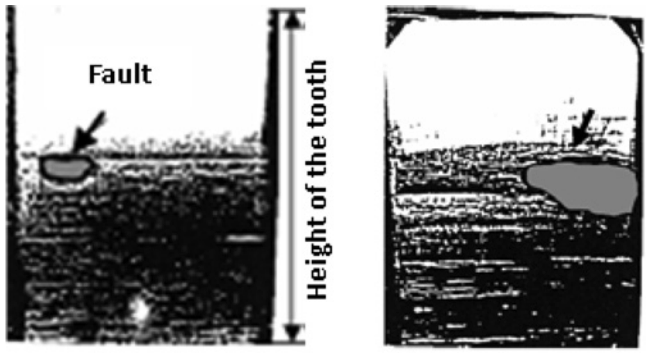

a *b*

Fig. 5 *Tooth 16 in the*

a 10th day
b 11th day

where f_1 is the rotation frequency of the 1st wheel, f_2 is the rotation frequency of the 2nd wheel, Z_1 is the number of teeth of the 1st wheel and Z_2 is the number of teeth of the 2nd wheel.

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 (Fig. 5). The different dynamic parameters of the gear system and geometrical parameters of the gear and pinion are given in Table 1 [13–16].

4.2 Results and discussions

Given the large number of data (60160 samples), it is difficult to treat them all. Hence, 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 16.67 Hz and the sampling frequency $f_{sap} = 20$ KHz. To calculate the number of samples covering the period, we divide the rotation period T on the sampling period. Hence, 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. 6.

We note that during the first eleven days, the temporal representation of the vibration meshing signal does not give further evidence characterising the occurrence of a fault.

In contrast, at the twelfth and the last days, the representations are different; which indicates the presence of a defect because of the deterioration of a tooth. The

Table 1 Geared system data

Parameter	Pinion	Gear
speed, rpm	1000	952
number of teeth	20	21
face width, m	0.015	0.03
shaft diameter, m	0.092	0.110
module, m	0.01	0.01
pressure angle	20°	20°
addendum coefficient	1.0	1.0
dedendum coefficient	1.4	1.4
mass, N	36	80
shaft torsional stiffness, N m/rad	1917	3383
bearing stiffness, N/m	10^8	10^9
shaft viscous damping coefficient, N s/rad	0.2688	0.3571
bearing viscous damping coefficient, N s/m	8740.15	8740.15
drive torque, N m	200	

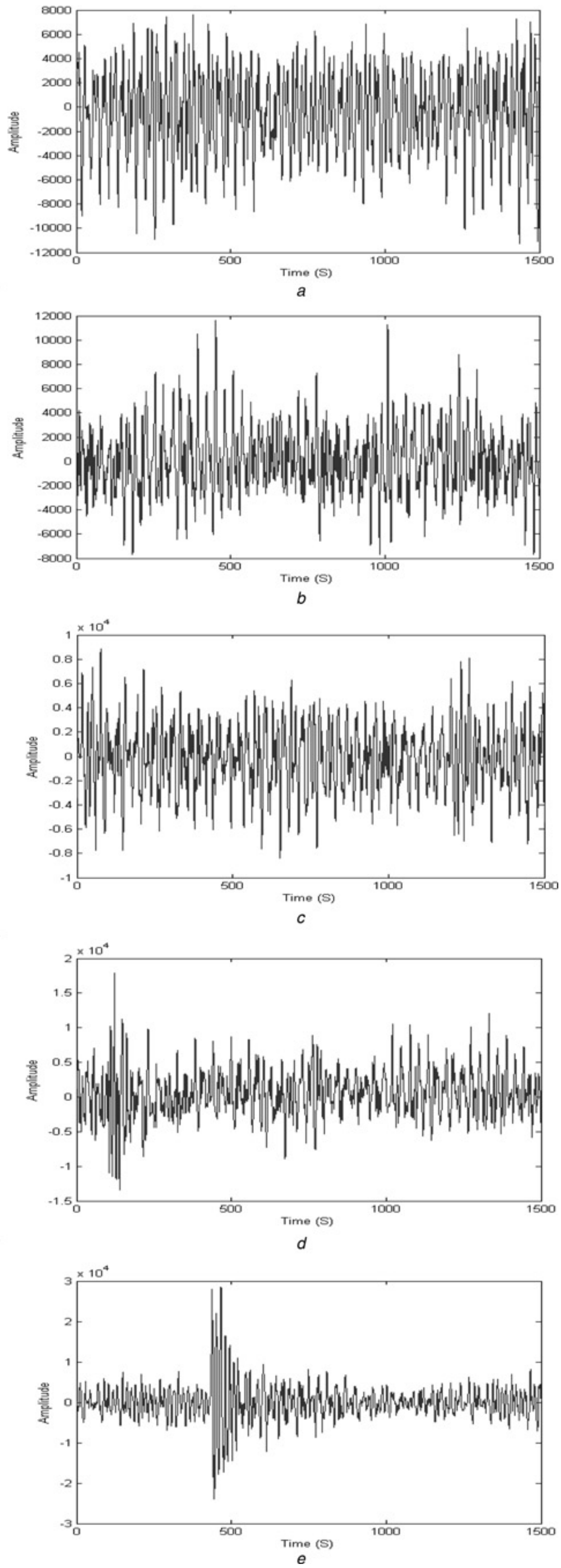

Fig. 6 *CETIM gear vibration signals recorded during*

a 8th day
b 9th day
c 10th day
d 11th day
e 12th day. Displaying over two periods of rotation relative to the pinion

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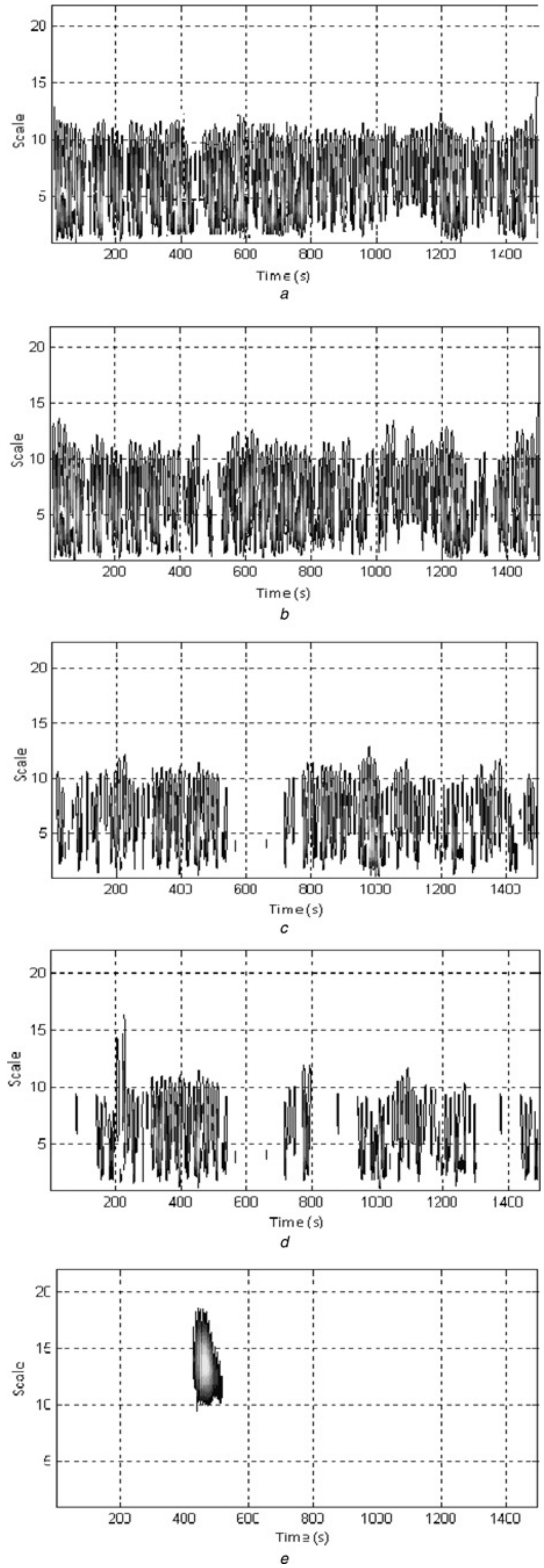

Fig. 7 *AMW scalograms of CETIM gear vibration signals using the maximum Morlet wavelet coefficients as a cost function*

a 8th day
b 9th day
c 10th day
d 11th day
e 12th day

vibration signal retains the same shape until the 12th day during which the fault appears. We note that a shock occurs at a time corresponding to the rotation period of the gear system and having very high amplitude compared with the signal collected during the other days. These observations allow the diagnosis of a fault in the 12 and 13th days.

The representation of the vibration signal using the AMW is the goal of our work. This representation is used to early detect the failure of gears in the time-scale domain and try to identify it. The scalograms obtained by the application of the AMW, using the maximum Morlet wavelet coefficients as a cost function, on the vibration signal emitted by the gear system during the 13 days of experimental test are shown in Fig. 7. The optimal parameter values are $f_b = 15.8$, $f_c = 0.69$.

In the AMW domain, the coefficients are stable and have similar magnitudes until the 9th day.

At the 10th day, the coefficients start changing their behaviour. We observe the absence of a part of the band on the AMW 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 AMW coefficients.

5 Comparison of our technique with other techniques proposed in the literature

Several techniques, based on AMW, have been proposed in the literature for feature extraction of gear vibration signals [52, 56, 57]. Most of these methods utilise modified Shannon wavelet entropy as a cost function to optimise central frequency and bandwidth parameter of the Morlet wavelet in order to achieve optimal match with impulse components.

The modified Shannon wavelet entropy is computed by [56]

$$H^k(f_b) = -\sum_{i=1}^{M} P_i^k \log P_i^k, \quad \sum_{i=1}^{M} P_i^k = 1, \qquad f_c = k \in [J, K] \tag{8}$$

where P_i^k is the distribution sequence obtained from wavelet coefficients. P_i^k is calculated by

$$P_i^k(f_b) = |W_x(m, n)| / \sum_{j=1}^{M} |W_x(m, n)| \tag{9}$$

These approaches perform well when applied to feature extraction of vibration signals resulting from rolling element bearing defects or gearbox faults. However, these techniques have not been applied to early detect the fatigue cracks in these rotating mechanical elements.

In this paper, we have applied the AMW based on the modified Shannon wavelet entropy to the vibration signals of the gear reductor provided from CETIM. This application will be used to compare the performances of our technique, based on the maximum values of Morlet wavelet coefficients as a cost function, with the methods based on the modified Shannon wavelet entropy. The optimal parameter values are $f_b = 20.2$, $f_c = 0.5$.

Fig. 8 represents the scalograms obtained by the application of AMW, based on the modified Shannon wavelet entropy, on the vibration signal emitted by the CETIM gear system during the 13 days of experimental test. From this figure, the tooth crack failure of gearbox has not been observed until the 12th day where the AMW

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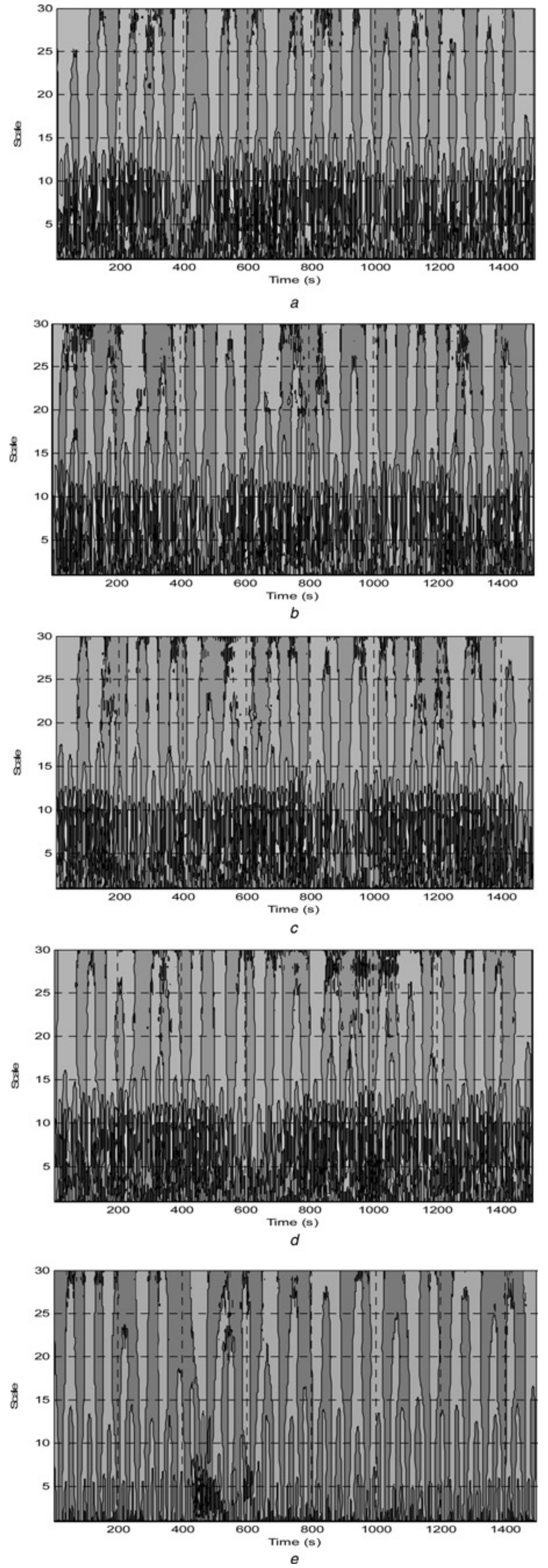

Fig. 8 *AMW scalograms of CETIM gear vibration signals using modified Shannon wavelet entropy as a cost function*

a 8th day
b 9th day
c 10th day
d 11th day
e 12th day

coefficients change their behaviour. Hence, there is no early indication of the presence of a gear defect.

From this example, it can be seen that our method, based on maximum values of Morlet wavelet coefficients as a cost function, is more effective for the early detection of the presence of a gear defect than the techniques based on modified Shannon wavelet entropy. In fact, our method can early indicate the presence of a gear defect at the 10th day by observing the absence of a part of the band on the AMW scalogram (Fig. 7).

6 Conclusions

In the present contribution, a new fault diagnosis approach for gear systems was proposed. This approach is based on the AMW, which is used to early detect the presence of defects by searching a rupture signature in the vibration signal delivered from a gear transmission system. Hence, a procedure is proposed in this work, in order to adapt the mother Morlet wavelet with the gear vibration signal by setting parameters of the wavelet to balance the time–frequency resolution. The output of this procedure is an optimal pair of parameters that results in the best time–frequency resolution for the given gear vibration signal. The translation invariance of the AMW allows the definition of a rupture signature. Consequently, the fault detection problem will be considered just as a simple signature search in the time-scale domain using scalograms.

In our work, the AMW is first applied to detect a defect from a simulated process obtained by the product of a deterministic sinusoidal signal with a Gaussian white noise. We note that the defect signature in the AMW coefficients domain (scalogram) is detected at the right time. Through the application of the proposed AMW method to the simulated signal, the effectiveness of the proposed technique for detecting the defect in the signal with the presence of a multiplicative noise has been proved. Secondly, for real gear system, the AMW is applied to early detect the gear fault. The scalograms obtained by the application of the AMW on the vibration signal emitted by the gear system during the 13 days of experimental test have shown that the wavelet transform coefficients are stable and have similar magnitudes until the 9th day. At the10th day, the coefficients start changing their behaviour through the observation of the absence of a part of the band on the AMW 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 AMW coefficients. Thus, these results have shown the powerful features of the proposed technique in the early detection of gear faults. The proposed method is simple to implement.

Future work will investigate the proposed methodology on a range of more representative data. However based on this initial investigation, it is believed that the proposed methodology offers an intuitive and cost effective approach which can be used to visualise the condition of a gearbox and serve to support maintenance decisions.

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