Multilevel Decomposition of the Envelope for Faults Detection in Gears

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Abstract— **The early gears faults detection remains a major problem, particularly when gears are submitted to phenomena non-stationary due to defects. The idea of this paper is to apply a multilevel decomposition technique based on EMD in the aim to detect and isolate faults in gears. Firstly, we determinate the upper envelope of a most dominant intrinsic mode function (IMF). Then, we injected an external signal, known as a masking signal or a pseudo-fault signal to isolate different fault frequencies, present in the envelope. Finally, we reapplied the EMD. An indicator of damage metric and Kurtosis are used to detect the presence of faults. The proposed method is evaluated on vibratory signals from the test bench, CETIM. Our results showed the occurrence of a teeth defect on gear on the 6th and 8th day. This result agrees with the report of the appraisal made on this gear system.**

Keywords—vibratory signal; empirical mode decomposition; signal assisted fault detection; masking signal; enveloping

I. Introduction

A machine consists of a set of organs or parts, assembled and intended to perform a specific function (training, braking, etc.). The defects of these organs have a detrimental influence on certain measurable physical parameters, such as vibrations, noise, electrical currents, pressure, etc. A mechanism can't operate without constraints that manifest in the form of vibrations and all change in these constraints will result in a change in the amplitude or the vibration frequencies. Thus, the defects can be detected early if we follow the vibratory levels. This monitoring avoids a breakdown that can paralyze part of the plant and lead to a financial loss important. In effect, a default located on a gear tooth will produce periodic shocks to each contact of the faulty tooth against any other. Such shocks can be of small amplitudes when the fault is born. Such failures are progressing rapidly to the rupture [1]. However, the noise introduced in the signals by various disturbances produces an effect of a mask that makes the faults detection difficult for the emerging faults often impossible because the characteristics are often very low and hidden by the noise. To remedy this, several methods operating in the time domain [2] [3] and in the frequency domain [4] [5] [6] [7] [8] have been developed. In this paper, we used a method built upon the principles of empirical mode decomposition (EMD) [9] [10] which are based on the analysis of the upper envelope and the injection of an external signal for the separation of faults. The assumption of this technique is that it is necessary to determine the dominant IMF which helped us to determine the faults. The indicator of injury metric is used as an indicator to detect the day of the appearance of faults.

II. External signal assisted EMD

In rotating components local defects generate periodic impacts within the system which excites resonance vibration modes of a structure. The key element in detecting local defects is that only high frequency resonance modes appear in the measured waveform because lower resonant frequency will be masked by other vibration components. The aim of the method presented here is to detect the local defect.

External signal assisted EMD is a masking signal, used to separate fault mode signal from the dominant envelope. This is accomplished by applying a series of pseudo fault signals built from known system fault frequencies. The dominant envelope acquires signatures generated from system faults mixed with wideband structure-borne noise and other high frequency measurement noises. It's used for fault detection and localization. The technique consists in decomposing the vibratory signal using EMD to extract different intrinsic modes [10]. Selecting the most dominant IMFs with an energy rank. This is based on the hypothesis that vibrations produced by impacts have higher energy [11].

The energy E_{Ci} of an IMF, is calculated as:

$$Ec_i = \sum_{t=t_l}^{t=t_l+T} C_i^2(t) \quad (1)$$

$C_i(t)$ is the i_{th} IMF of the original signal, and T is the time duration of the analysed signal.

The envelope of this dominant IMF is determinate. The second decomposition of the level is achieved by injecting an external signal known us a pseudo-default signal (PFS) to the envelope of the most dominant IMF [12]. A masking signal is built from known system fault frequencies. The goal of the external signal use is to isolate the different fault frequencies present in the envelope. This masking signal serves two purposes:

- Solves the problem of the mixture in the inherent mode.
- Extract relevant fault information.

It should be noted that a masking signal is applied to the dominant IMF only if its frequency spectrum has a peak near one of the fault frequencies.

III. External signal-EMD Algorithm

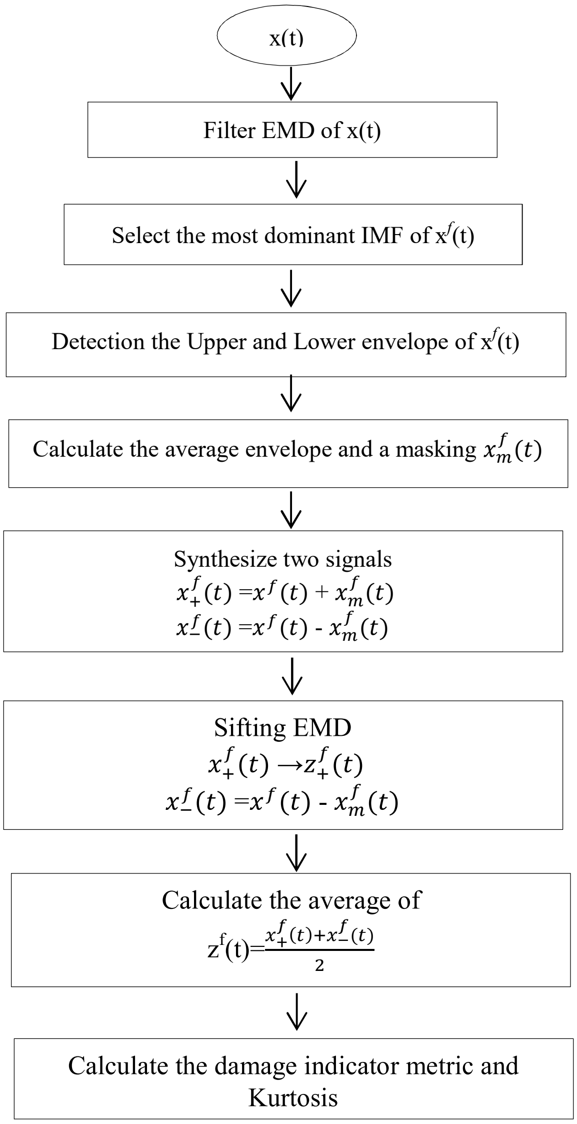

Fig. 1. The flowchart of the algorithm

The algorithm (fig1) proceeds in five steps [12]:

1. Identify the dominant IMF , $x^f(t)$ using EMD decomposition and the energy factor E_{Ci}

The envelope of the dominant IMF contains information about the faults, but it is modulated by multiple sources of fault and noise.

2. Build a masking signal , $x_m^f(t)$

The masking frequency signal is determined by system fault frequencies and must be slightly higher than the fault frequency signal, to allow for uncertainties associated with analytical fault frequencies

$$x_m^f(t) = A_m \times \sin(2\pi \alpha_F f_m t) \quad (2)$$

$$A_m = \alpha_A \times \max(|C_i(F)| \quad (3)$$

$C_i(F)$ is Fourier transform of the i^{th} IMF $C_i(t)$

α_A: amplitude factor of the masking signal depending on the frequency ratio and amplitude of signal components, equal to 1.6 in our case.

f_m : the higher frequency of the i^{th} IMF

α_F:1.2

3. Determine two versions of signals

$$x_+^f(t) = x^f(t) + x_m^f(t) \quad (4)$$

$$x_-^f(t) = x^f(t) - x_m^f(t) \quad (5)$$

4. Effect the sifting of $x_+^f(t)$ and $x_-^f(t)$ to obtain $Z_+^f(t)$ and $Z_-^f(t)$
5. Extract from the original signal the higher frequency intrinsic function and to get back the original component, the added masked signal is then removed from the extracted IMF
   $z^f(t)$: fault indicator signal
6. Calculate the damage indicator metric

$$\Psi = \left\| z(t) \right\|_2 = \left(\sum_{t=t_1}^{t=t_1+T} z^2(t) \right)^{1/2} \quad (6)$$

and the Kurtosis

$$K = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{x_i - \bar{x}}{\sigma} \right]^4 \quad (7)$$

IV. Experimental Tests

A. Signal Database

The technique proposed is evaluated on vibratory signals provided by CETIM. The recordings were made on a gear system with a report 20/21. In the course of the experience, the gearbox worked continuously for 12 days with a mechanical assessment daily, until the gear is deteriorating at an abnormal state. The signals have been acquired once all 24 hours each record lasted 3 seconds and contained 60000 samples. The rotational frequency is equal to 16.67 Hz, the number of teeth of the wheel is equal to 21, the number of teeth of the pinion is equal to 20 teeth, the meshing frequency is 333 Hz and a sampling frequency of 20000 Hz. The Rotation frequency of the wheel is equal to 15.87 Hz. These signals have already been used on several occasions to demonstrate the diagnostic procedures [2]. Table 1 indicates the status of the gearbox over time.

TABLE I. Pinion Status Evolution.

Day	Status	Day	Status
1	No Problem	7	No evolution on tooth 1/2
2	No Problem	8	No evolution on tooth 1/2 Beginning Spalling on tooth 15/16
3	No Problem	9	evolution on tooth 15/16
4	No Problem	10	evolution on tooth 15/16
5	No Problem	11	evolution on tooth 15/16
6	Spalling on tooth 1/2	12	Spalling on entire tooth 15/16

V. Results and discussion

Fig. 2 and fig.3, show the temporal and spectral representation of a vibratory signal, early defect detection is not possible. The defect appears only on the 11th day because in early fault detection the features are often very weak and masked by the noise.

From fig.3, we can see a meshing frequency 330 Hz and its multiples. Fig. 4 shows the temporal and spectral representations of a most dominant IMF. The meshing frequency 330h Hz appears too.

To compare the performance of the proposed technique, classical EMD was also applied. Fig. 5 and fig.6 present the evolution of metric damage indicator and kurtosis value as a function of the acquisition day; without treatment, after analysis by classical EMD and after the application of fault model signal-EMD.

The evolution of the graphs in fig.5 of the damage metric indicator shows that applying EMD, we detect the appearance of default on the 9th day. The external signal assisted EMD (PFS-EMD) method detected the appearance of a first defect on the 6th day and a second on the 8th day. These findings become solid if we look at fig.6 where the evolution of kurtosis is more significant on the 6th and 8th days and clearly indicating the appearance of two faults.

According to fig.5 and fig.6, PFS-EMD clearly allowed the detection of a first defect on the 6th day and another one on the 8th day both with the indicator of metric damage and kurtosis which is in line with the report of expertise.

Using EMD, fault detection on the 6th day is difficult to see and not detect the 8th day.

Indeed, the first application of EMD determines the IMFs. The IMF with a peak frequency in the vicinity of fault frequency which corresponds to the rotation frequency of the wheel (f= 15.87 Hz) in our case is classified a dominant IMF. The pseudo fault signal corresponding to fault characteristic frequency 15.87 Hz is generated and second level of EMD is used to further demodulate envelope of the dominant IMF and decompose it into different fault indicator signals. This allowed us to detect clearly the first and second defect which is a fault in the form of chipped teeth.

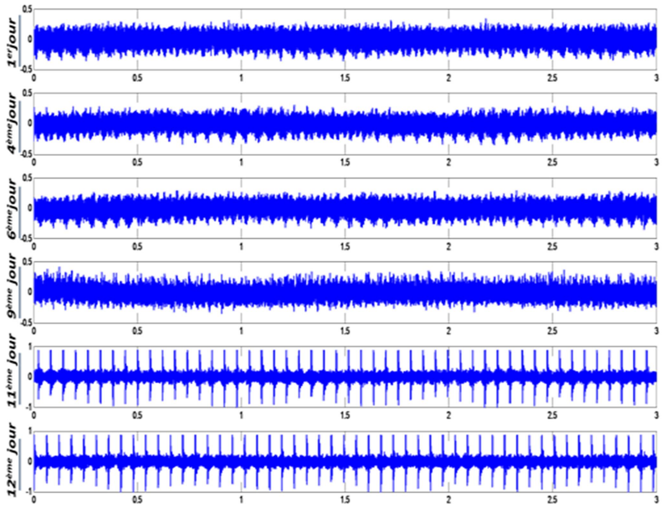

Fig. 2. Temporal representation of a vibratory signal 1st, 4th, 6th,9th, 11th and 12th day

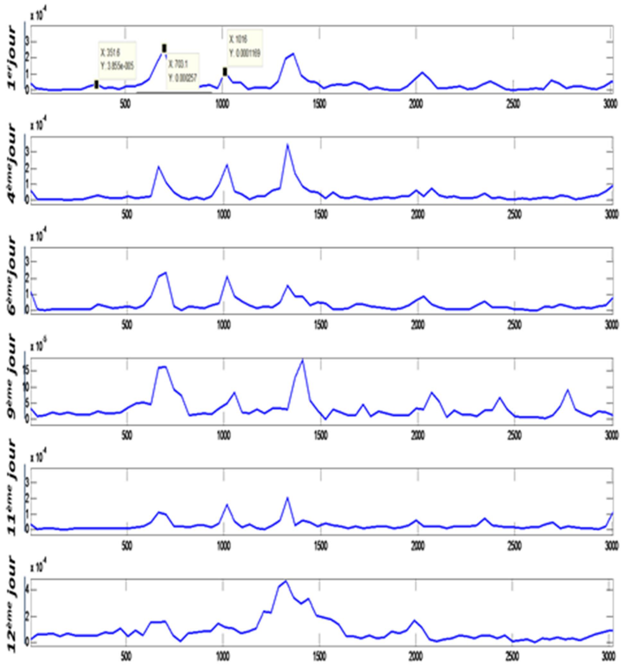

Fig. 3. Spectral representation of a vibratory signal 1st, 4th, 6th,9th, 11th and 12th day

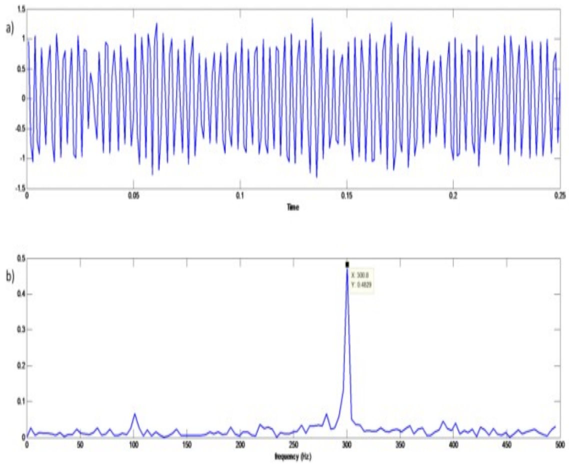

Fig. 4. Dominant IMF : Temporel and spectral representation

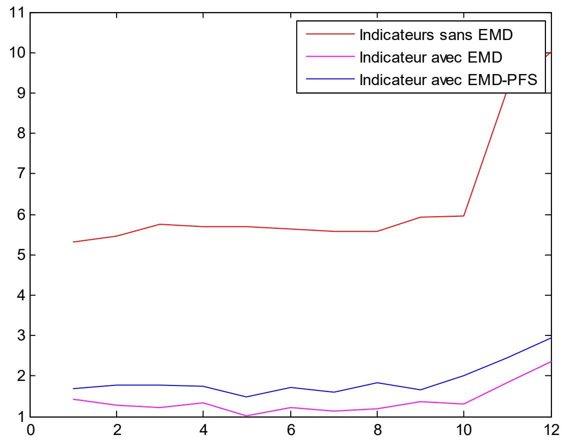

Fig. 5. indicator of metric damage
(-without treatment,-with EMD , - PFS-EMD) ,

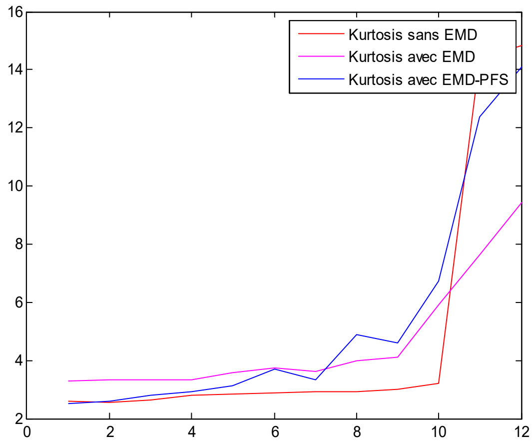

Fig. 6. indicator of kurtosis
(-without treatment,-with EMD , - PFS-EMD)

VI. Conclusion

We have carried out studies on gear signals from the CETIM test bench whose objective is to detect and isolate defects using the external signal-EMD technique. The latter is based on the detection of defects on the most dominant IMF and the application of a masking signal in order to isolate the defects. The test results showed that the PFS-EMD technique allowed us to isolate the defect in case the fault frequencies are close. Metric and kurtosis damage indicators, calculated, showed the robustness of the external signal-EMD technique. The latter allowed us to conclude that the external signal assisted EMD makes it possible to better detect the defect compared with the EMD.

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