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Early Detection of Bearing Faults by the Hilbert-Huang Transform

Abdenour Soualhi¹

LASPI-EA 3059
Université Jean-Monnet
Roanne, F-42300, France

Kamal Medjaher², Noureddine Zerhouni²

FEMTO-ST
ENSMM
Besançon, F-25000, France

Hubert Razik³

Ampère - UMR 5005
Université Lyon1
Villeurbanne, F-69622, France

¹abdenour.soualhi@univ-st-etienne.fr

²[kamal.medjaher,noureddine.zerhouni]@ens2m.fr

³hubert.razik@univ-lyon1.fr

Abstract— The operation of bearings usually results in a dynamic behavior generating stationary and non-stationary vibration signals mixed with an amount of background noise. Therefore, the condition monitoring of bearings becomes difficult since the purpose is to extract health indicators able to detect the appearance of faults, track their evolution and predict the bearings' remaining useful life.

The aim of this paper is the introduction of a new approach for the health monitoring of bearings. This approach is based on health indicators extracted from raw vibration signals filtered by the Hilbert-Huang transform. The proposed approach is composed of three steps. The first step uses the empirical mode decomposition to separate each vibration signal into different intrinsic mode functions (IMFs), where each IMF is located within a specific frequency band. The second step extracts instantaneous amplitudes and frequencies for each mode in order to identify its frequency band. Finally, the third step selects the interesting IMFs according to the characteristic frequencies of the bearing failures. The Hilbert marginal spectrum of the selected intrinsic mode functions are then considered as health indicators. The proposed approach is validated by real data taken from the PRONOSTIA experimental platform.

Keywords— Beating, feature extraction, condition monitoring, fault detection, fault diagnostic, time-frequency analysis, empirical mode decomposition, Hilbert transform.

I. INTRODUCTION

Bearings are mechanical components used in different industrial equipments. They can be considered as critical components as their failures reduce the equipments' reliability and availability, and increase the risk of human accidents. Furthermore, their failures generate additional maintenance costs and produce a negative environmental impact. To face this situation, the implementation of a Condition-Based Maintenance (CBM) seems to be an efficient strategy [1]-[5].

The analysis of vibration signals are relevant in performing a CBM on bearings because they allow characterizing their most faults by extracting health indicators. These indicators are obtained through signal processing methods, which can be classified according to the vibration signal form: stationary or non-stationary. The stationary signals are analysed by using the well-known temporal and/or frequency methods [6]-[8], whereas the non-stationary signals are processed by using time-frequency methods [9]-[11]. The temporal analysis is

historically the oldest method; it analyses the temporal characteristics of the acquired signal in order to extract statistical health indicators. Among these indicators, one can find the Root Mean Square (RMS) that measures the average energy of the signal, the peak to peak value which measures the maximum amplitude between the extreme values of the signal, the kurtosis that measures the impulsive nature of the signal, etc. The assumption behind the temporal analysis is that any fault occurrence causes significant change in the statistical features of the signal. This allows detecting and tracking the degradation of a bearing. However, the presence of noise in the signal makes difficult filtering the vibration signal. This drawback prevent early detection of faults. In this paper, a solution is proposed to solve this problem. The idea is to remove noised vibration signals that are not related to the failure of a bearing by using the empirical mode decomposition (EMD) and locating the contribution of the characteristic frequencies of bearing failures (inner race, outer race, balls) by computing the Hilbert Marginal Spectrum (HMS). The HMS, obtained by the Hilbert transform which is a time-frequency analysis method, is used as a health indicator to detect, diagnose and track the degradation of bearings. This approach removes noised signals that are not related to the failure of ball bearings and therefore allows extracting health indicators that maximize the chances of early detection of incipient faults. The combination of the empirical mode decomposition and the Hilbert transform is known as the Hilbert-Huang Transform [12], [13].

This paper is organized as follows. After the introduction section, section II presents the main steps of the proposed approach. The purpose of section III is to introduce new health indicators for the health monitoring of bearings. These indicators are extracted from the analysis of vibration signals by using the Hilbert-Huang transform. Section V validates the proposed approach on real data taken from the PRONOSTIA experimental platform. Finally, section VI concludes the paper.

II. FEATURE EXTRACTION BY HILBERT-HUANG TRANSFORM

The Hilbert-Huang transform is an emerging technique for the signal processing designed to analyse non-stationary signals [14]. This technique has been used in many applications, such as biomedical signal processing [15], geophysics [16], image processing [17], fault diagnostic [18],

etc. In order to facilitate the reading of this paper, the Hilbert-Huang transform (HHT) is first presented followed by an introduction of the HMS. HHT is performed in two steps. The first step uses the EMD to identify the intrinsic oscillatory mode in each time location from a signal. This intrinsic oscillatory mode is called the intrinsic mode function (IMF). The second step apply the Hilbert transform on the IMF in order to extract the instantaneous frequencies and amplitudes of the signal, necessary to compute the HMS.

A. Empirical mode decomposition

The EMD decomposes a signal, denoted $x(t)$, into a set of IMFs. Generally, the component with the shortest period (high frequency) is identified and decomposed in the first IMF. The components of long periods (low frequencies) are then order in the next IMFs. The advantage of this technique is that is possible to isolate the frequency bands of interest.

The EMD decomposes the signal $x(t)$ by following four steps:

- 1- Identification of all local extrema, then connecting all local maxima by a cubic spline to form the upper envelope.
- 2- Repeating the same procedure for the local minima in order to produce the lower envelope.
- 3- The upper envelope $x_{up}(t)$ and the lower envelope $x_{low}(t)$ allow calculating the mean envelope $x_{mean}(t)$:

$$x_{mean}(t) = \frac{x_{up}(t) + x_{low}(t)}{2} \quad (1)$$

The removing of the mean envelope from the signal $x(t)$ allow us obtaining a first component denoted $\delta_{10}(t)$:

$$\delta_{10}(t) = x(t) - x_{mean}(t) \quad (2)$$

If $\delta_{10}(t)$ has exactly one zero between any two consecutive local extrema or has zero "local mean", then δ_{10} can be considered as the first IMF of $x(t)$.

- 4- If $\delta_{10}(t)$ does not satisfy the previous constraints, then the signal $x(t)$ is replaced by $\delta_{10}(t)$ and the steps 1 to 3 are repeated. A second component denoted $\delta_{11}(t)$ is obtained:

$$\delta_{11}(t) = \delta_{10}(t) - x_{mean}(t) \quad (3)$$

This process is called sifting process and is repeated successively (k times) on $\delta_{ik}(t)$ until the value between the upper and lower envelope is close to zero at each point. The i^{th} component $\delta_{ik}(t)$ is formulated as follows

$$\delta_{ik}(t) = \delta_{i(k-1)}(t) - x_{mean}(t) \quad (4)$$

$x_{mean}(t)$ is the mean of the upper and lower envelope of $\delta_{i(k-1)}$. The first IMF, denoted $\Omega_1(t)$ with $\Omega_1(t) = \delta_{1k}(t)$, represents the component of the shortest period (high frequencies) of the signal $x(t)$.

Extracting $\Omega_1(t)$ from $x(t)$ gives a first residual denoted $r_2(t)$:

$$r_2(t) = r_1(t) - \Omega_1(t) \quad (5)$$

with $r_1(t) = x(t)$.

This provides the n IMFs of the signal $x(t)$ by using the following expression:

$$r_n(t) = r_{n-1}(t) - \Omega_{n-1}(t) \quad (6)$$

When the signal $r_n(t)$ becomes a monotonic function, the decomposition process can be stopped.

The extraction process of IMFs is summarized in fig.1. The IMFs $\Omega_1, \Omega_2, \dots, \Omega_n$ include different frequency bands ranging from the top to bottom. The frequency band contained in each component is different from a component to another, and these frequencies change according to the signal $x(t)$.

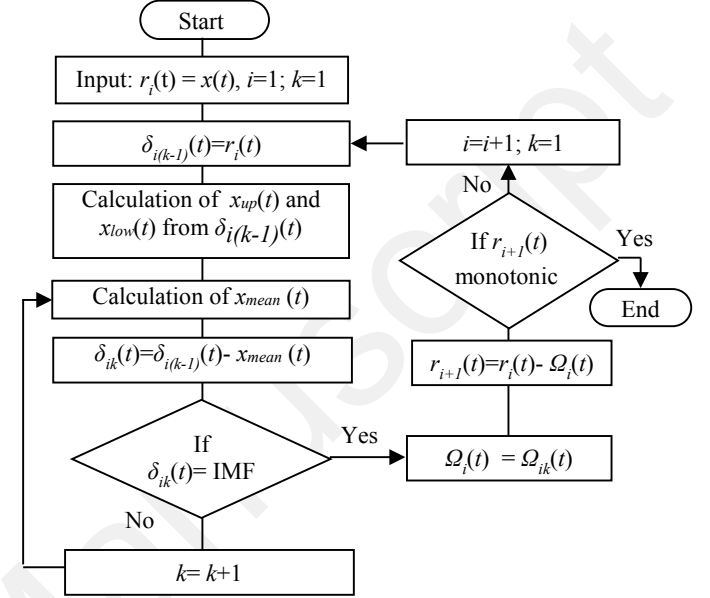


Fig.1. Flowchart of the empirical mode decomposition process.

B. Hilbert transform

The Hilbert transform can be considered to be a filter which simply shifts phases of all frequency components of its input by $-\pi/2$ radians. An analytic $x(t)$ can be constructed from a real-valued input signal $x(t)$: $x^A(t) = x(t) + jx^h(t)$ where, $x^A(t)$ is the analytic signal constructed from $x(t)$ and its Hilbert transform. $x(t)$ is the input signal and $x^h(t)$ is the Hilbert transform of the input signal. The angle of the complex signal gives the instantaneous phase, and its derivative, the instantaneous frequency. The aim is to extract the instantaneous frequency and amplitude of each IMF in order to identify their corresponding frequency band. The analytic form of an IMF, denoted $\Omega_i^A(t)$, is defined as:

$$\Omega_i^A(t) = \Omega_i(t) + j\Omega_i^H(t) = a_i(t)e^{j\theta_i(t)}, \quad 1 \leq i \leq n \quad (7)$$

where n is the number of IMFs and $\Omega_i^H(t)$ is the Hilbert transform of $\Omega_i(t)$, given by:

$$\Omega_i^H(t) = \frac{1}{\pi} P \int \frac{\Omega_i(s)}{t-s} ds \quad (8)$$

where P is the Cauchy principal value.

From (7) and (8), the instantaneous amplitude $a_i(t)$ and phase $\theta_i(t)$ are given as follows:

$$a_i(t) = \sqrt{\Omega_i^2 + \Omega_i^H 2} \quad (9)$$

$$\theta_i(t) = \tan^{-1} \left(\frac{\Omega_i^H}{\Omega_i} \right) \quad (10)$$

From the instantaneous phase $\theta_i(t)$, the instantaneous frequency $f_i(t)$ can be obtained by using the following formula:

$$f_i(t) = \frac{1}{2\pi} \frac{d\theta_i(t)}{dt} \quad (11)$$

C. The Hilbert Marginal spectrum (HMS)

As said in the abstract section, the first step of the proposed approach uses the EMD to decompose the signal $x(t)$ into several IMFs. The second step extracts instantaneous amplitudes and frequencies for each IMF to identify their corresponding frequency band and the third step calculates the energy density at specific frequencies to select the IMFs of interest and extract the health indicators.

The Hilbert energy density is defined as the square of the amplitude:

$$H_i(f, t) = a_i^2(f_i, t) \quad (12)$$

where $H_i(f, t)$ represents a time-frequency distribution obtained from the i^{th} IMF of the signal $x(t)$ and $a_i(f_i, t)$ combines the amplitude $a_i(t)$ and the instantaneous frequency $f_i(t)$ of the signal.

$H(f, t)$ gives a local value of energy in a time-frequency representation. This allows extracting the joint probability density $p(f, t)$ of the frequency and amplitude from the whole original series $a_i(t)$ and $f_i(t)$ for all IMFs, $i = 1, \dots, n$. Then, the HMS can be estimated as follows:

$$h_i(f) = \int H_i(f, t) dt = \int a_i^2(f_i, t) dt \quad (13)$$

III. SIMULATION RESULT

To show the effectiveness of the EMD and the HMS to isolate the frequency bands of interest, consider the signal of fig.2:

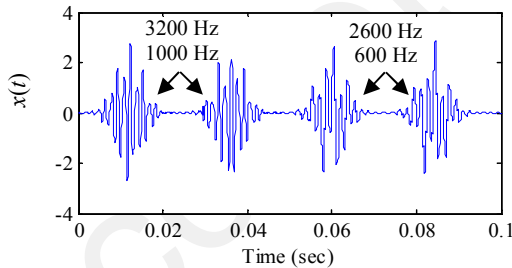


Fig.2. Temporal representation of the non-stationary signal $x(t)$.

Figure 2 shows a signal $x(t)$ oscillating at the frequencies 600, 1000, 2600 and 3200 Hz. The EMD is used to extract the IMFs of $x(t)$ (see fig.3.a and c) and the corresponding HMS are used to locate the high frequencies and the low frequencies components (see fig.3.b and d). From the fig.3.b, one can see that the HMS applied to the first IMF identifies the high frequency components 2600 Hz and 3200 Hz. The HMS applied on the second IMF (see fig.3.d) identifies the medium

and low frequencies components: 600 Hz and 1000 Hz. These results are very interesting because if we consider the medium and low frequency components as the characteristic frequencies of a fault, then one just needs to monitor the HMS of the second IMF to locate and track the degradation of the bearing.

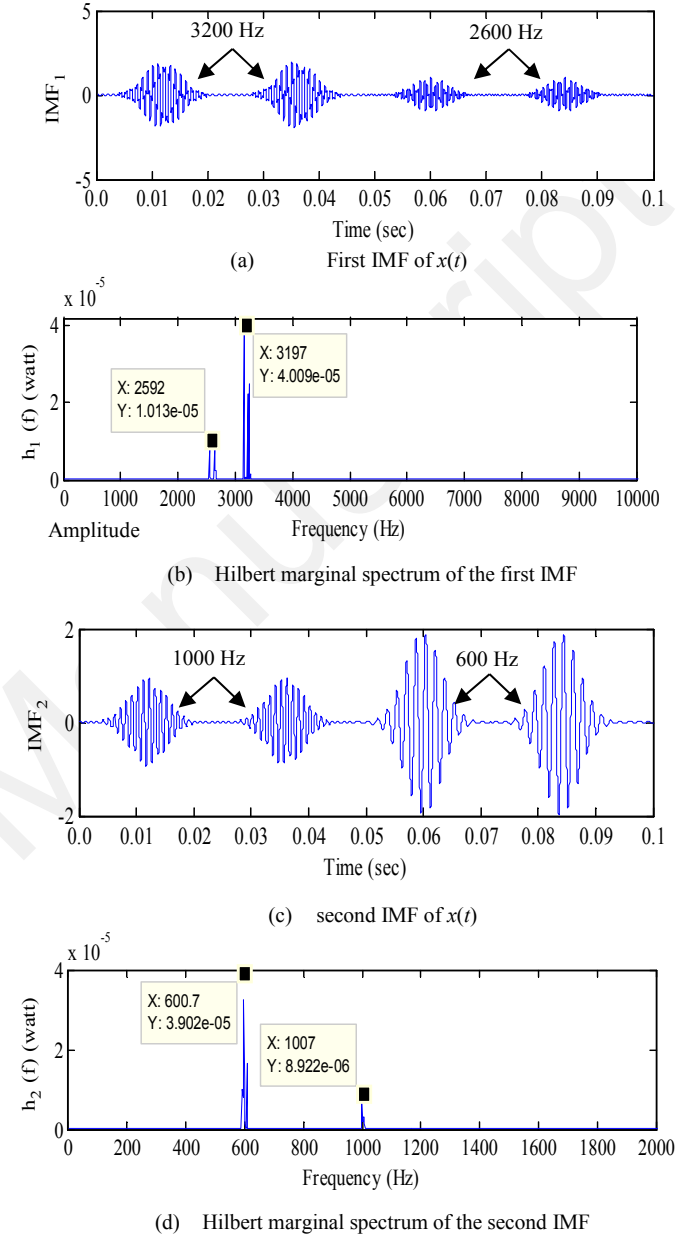


Fig.3. Hilbert marginal of a non-stationary signal

IV. EXTRACTION OF HEALTH INDICATORS

Once the HMS is defined, it is possible to select the IMFs gathering the characteristic frequencies of a given fault. This step can be assimilated as a step of IMF selection and health indicators extraction. To select the IMFs and extract the health indicators, it is necessary to know the characteristic frequencies of each fault. In the case of ball bearings, these frequencies can be calculated according to the number of balls, the rotation speed, the ball and the pitch diameters. From these

geometric and operating data, three frequencies can be identified:

- Inner race frequency (f_{ir}):

$$f_{ir} = \frac{n_b}{2} \cdot f_r \cdot \left[1 + \frac{DB}{DP} \cdot \cos \psi \right] \quad (14)$$

- Outer race frequency (f_{or}):

$$f_{or} = \frac{n_b}{2} \cdot f_r \cdot \left[1 - \frac{DB}{DP} \cdot \cos \psi \right] \quad (15)$$

- Ball frequency (f_b):

$$f_b = \frac{DP}{DB} \cdot f_r \cdot \left[1 - \frac{DB^2}{DP^2} \cdot \cos^2 \psi \right] \quad (16)$$

where f_r is the rotation frequency, Ψ the contact angle, n_b the number of balls, DB the ball diameter and DP the pitch diameter of the bearing.

The IMF selection consists of selecting a set of IMFs $\Omega_i(t)$ $1 \leq i \leq n$ which has a HMS maximum around one, two or three of the characteristic frequencies. This can be formulated as follow:

$$\Omega_i(t) \rightarrow \max_{1 \leq i \leq n} [h_i(f_{or}, f_{ir}, f_b)] \quad (17)$$

where n is the number of IMFs that makes up the signal.

Note that in the case of bearings, the number of fault frequencies is equal to three and therefore the number of selected IMFs can vary from 1 to 3. For example, if we have only one selected IMF, this means that the HMS around the faults characteristic frequencies is maximal for only one IMF.

Each of the selected IMFs maximizes at least one HMS around one of the faults characteristic frequencies. Therefore, in the health indicators extraction, the HMS: $h_j(f_{or})$, $h_j(f_{ir})$ and $h_j(f_b)$ are considered as health indicators, where $1 \leq j \leq n$ is the index of the selected IMF which maximizes the HMS of one of the following frequencies: f_{or} , f_{ir} and f_b .

V. EXPERIMENTAL RESULT

A. The experimental test bed PRONOSTIA

The proposed approach is verified on experimental vibration signals taken from the test bed PRONOSTIA, designed and realized within FEMTO-ST institute [19]. The test bed is composed of a ball bearing (NSK 6804RS) installed on a shaft, as shown in fig.4. The characteristics of this bearing are given in table I.

The rotation speed of the shaft is fixed at 1800 rpm by an assembly of two pulleys and a toothed belt. A radial force of 4200 N is applied to the shaft and the bearing by a proportional pneumatic jack. Two accelerometers of type 3035B DYTRAN, spaced by 90° , are placed on the bearing. The first accelerometer is placed on the vertical axis and the second on the horizontal axis. The vibration signals are composed of 2560 samples recorded every 10 seconds with a sampling frequency equal to 25.6 khz.

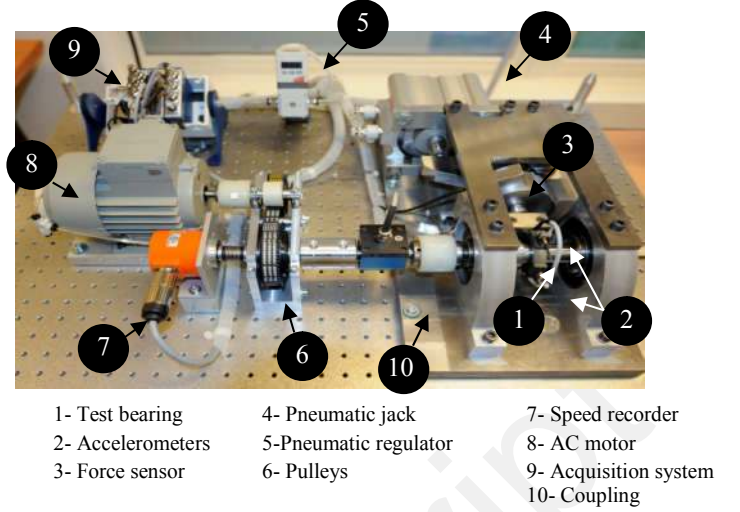


Fig.4. Test bed PRONOSTIA.

TABLE I
Characteristics of the studied bearing

Diameter of rolling elements (mm)	3.5
Number of rolling element	13
Diameter of the outer race (mm)	29.1
Diameter of the inner race (mm)	22.1
Bearing mean diameter (mm)	25.6

B. IMF selection

The analysed vibration signal corresponds to a defective bearing. The operating conditions (speed) applied to this bearing and its dimension allows calculating the three characteristic frequencies of faults:

Inner race frequency (f_{ir}): 221 hz

Outer race frequency (f_{or}): 168hz

Ball frequency (f_b): 215.48 hz

A set of IMFs are extracted from the vibration signal of the faulty bearing thanks to the EMD. These IMFs correspond to a decomposition of the vibration signal in specific frequency bands. The next step is the selection of the IMF of interest. This is done by calculating the HMS of each IMF. The comparison of the frequencies of the bearing fault (f_{or} , f_{ir} , f_b) with those identified in each IMF allows to select the IMFs corresponding to the faults. Thus, it is possible to detect the presence of a fault by monitoring the HMS around the frequencies (f_{or} , f_{ir} , f_b) in the selected IMFs. This methodology is illustrated in fig.5.

Figure 5 shows the HMS of each IMF extracted from the vibration signal of the faulty bearing. It is possible from this figure to identify the frequency band of each IMF. For example, if the first IMF is considered, one can notice that its frequencies are between 2896 hz and 12400 hz. For the IMF2, they are between 800 Hz and 6587 Hz. The frequencies of the third and fourth IMFs are between 400 hz and 3000 hz.

These four IMFs are considered as not informative. The HMS around the faulty frequencies of the IMF5 and IMF6 are high and can be therefore used for fault detection and identification.

By comparing the HMS of these two IMFs, one can observe a significant increase in the IMF6 compared to the IMF5, and

is mainly around the frequencies of the inner ring $f_{ir} = 221\text{Hz}$, the ball $f_b = 215.48\text{Hz}$ and the outer ring $f_{or} = 168\text{Hz}$. In this case, we can conclude that one IMF is sufficient to monitor the degradation of the tested bearing. However, the selection of IMF6 is not always valuable. This implies selecting for each new vibration signal the IMFs for which the HMS around the faults frequencies is high.

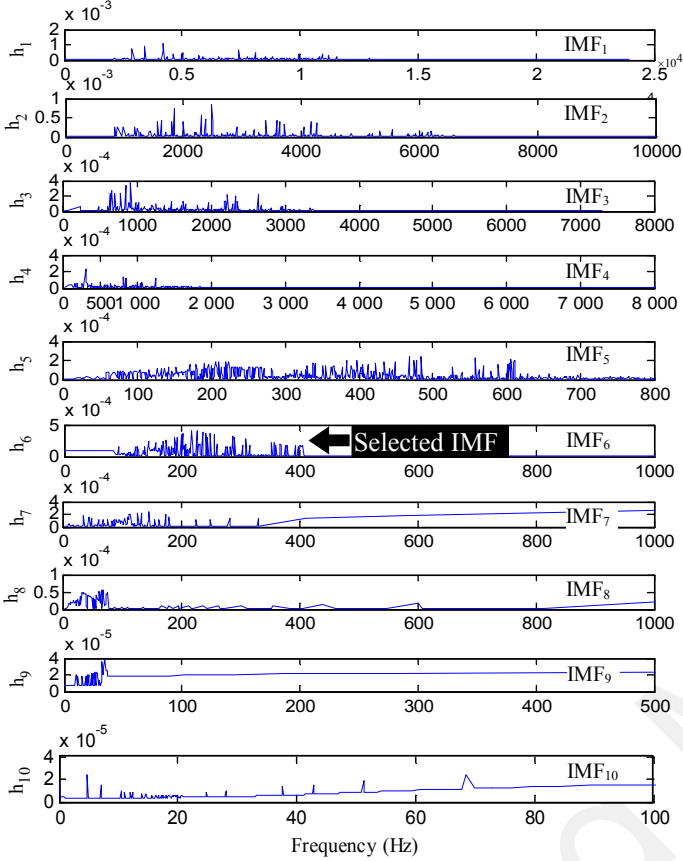


Fig.5. IMF selection according to the Hilbert marginal spectrum

Extraction of health indicators

The purpose of the previous sub-section is to show the applicability of the HMS to select the IMF of interest, extracted from a vibration signal collected on a bearing, according to the characteristic frequencies of faults. The proposed approach falls within the framework of diagnostic and therefore must provide an early detection of faults. Figures 6 (a, b, c) show the evolution of the HMS around the frequencies of the fault versus time.

The evolution of the RMS versus time is also added in fig.6.d in order to compare it with our health indicators. As we can see, the detection of an incipient degradation is different from an indicator to another. In the RMS, the beginning of the degradation is detected after 138 minutes of test. However, by calculating the HMS around the fault frequencies, it is possible to obtain an earlier detection than the RMS. Indeed, if we monitor the evolution of the HMS around the ball frequency (f_b), it is possible to detect a beginning of the degradation after only 118 minutes of test. This indication is

then followed by two other detections given by the HMS data around the frequencies of the inner race (f_{ir}) and the outer race (f_{or}) after 122 and 125 minutes of test respectively. These results show the effectiveness of this approach to extract health indicators able to monitor separately the critical components of a ball bearing.

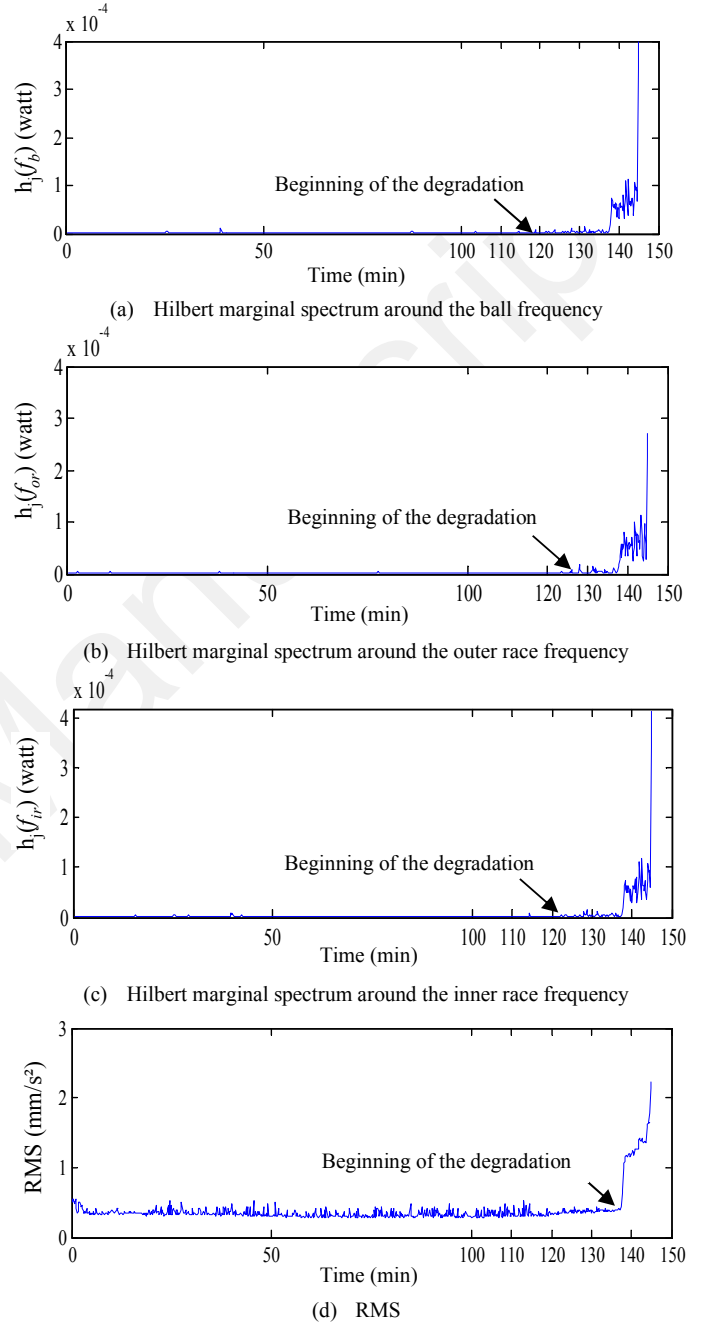


Fig.6. Evolution of the health indicators.

VI. CONCLUSION

Experimental study on bearings showed that their damages can be detected efficiently by means of time-dependent amplitudes and instantaneous frequencies resulting from the Hilbert transform. In this paper, the technique is extended by a process allowing automatic extraction of health indicators sensitive to the frequencies of faults in ball bearings. It is

based on the empirical mode decomposition and the Hilbert transform. The proposed approach consists of using the empirical mode decomposition to decompose the vibration signal into a sum of IMFs, where each IMF is located in a specific frequency band. The HMS, applied to the IMFs, can generate health indicators able to follow the progress of the degradation, but also to locate its origin. This approach was firstly applied on a synthetic non-stationary signal and then validated on experimental data. The results show the effectiveness of this approach for condition monitoring of bearings.

To assess its computational efficiency in processing the vibration signals, the experiments were conducted on a laptop with a processor frequency equal to 2.6 GHz and 4 GBytes flash memory. For the whole processed signals, the calculation time varied from 0.2 to 1.5 seconds. This confirms the applicability of the HMS for online monitoring. Furthermore, the proposed health indicators can be applied to other critical components and systems such as gearboxes, electric drives and wind turbines.

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