Advanced Feature Extraction Approach of Induction Machine Faults

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***Abstract*—this paper presents an efficient approach for treatment of vibration signals bearings failure in induction motor. We are developed a new approach for treatment non stationary signal dedicated to de vibration analytic signals of bearing fault to the induction machine monitoring. To extract a vectors forms to vibration signals from four bearing states (normal, rolling element defect, inner race defect and outer race defect) we are following two steps. The first step uses the Hilbert-Huang transform to decompose the signal into several IMFs by empirical mode decomposition. These IMFs represent the input signal in specific frequency bands given by the instantaneous frequencies. Next, these frequency bands are identified by the Hilbert marginal spectrum, which calculates the energy density at each frequency. Finally, the second step, we are using a Teager - Kaiser energy operator (TKEO) for extract the vectors forms.**

Keywords— Teager-Kaiser Energy operator; Empirical mode decomposition; vibration signals; Hilbert-Huang transform; bearing faults; induction motor.

I. INTRODUCTION

Recently, Huang et al. [1] have proposed a class a functions (oscillating components) called intrinsic mode functions (IMFs). To compute the frequency behavior of each IMF in time, the IF is estimated. A standard approach to this problem is to use the Hilbert transform (HT) and the related Gabors analytic signal [4]. An alternative approach developed by Maragos et al. [2] uses an energy-tracking operator, Teager energy operator (TEO), to first estimate the energy required for generating an AM-FM signal and then separate it into its IF and IA components [7],[8].

Knowing that The stationary signals are analyzed by using well- known temporal and/or frequency methods , whereas the non-stationary signals are processed by using time-frequency methods. Therefore we are developed a new approach for treatment non stationary signal dedicated to de vibration analytic signals of bearing fault to the induction machine monitoring. This approach based on Teager huang transformation (THT) to extracted a vectors forms from vibration signals from four bearing states (normal, rolling element defect, inner race defect and outer race defect) by following three steps. The first step uses use the Hilbert-Huang transform to decompose the signal into several IMFs by empirical mode decomposition. These IMFs represent the input signal in specific frequency bands given by the instantaneous frequencies. In the next step, these frequency bands are identified by the Hilbert marginal spectrum, which calculates the energy density at each frequency. Finally, the third step, we are using a Teager - Kaiser energy operator (TKEO) for extract vectors forms correspond a high energy density to the signals.

II. HILBERT-HUANG TRANSFORM

The Hilbert-Huang transform is an emerging technique for time-frequency signal processing designed to analyze nonstationary data, even within an oscillation cycle.

HHT is performed in two steps. The first step concerns empirical mode decomposition (EMD) [5], which decomposes the signal to obtain the intrinsic mode functions (IMFs) representing the average trend of the signal. Each of these IMFs is located in a specific frequency band. The second step deals with the Hilbert transform, which is applied to the IMFs in order to extract instantaneous frequencies and instantaneous amplitudes of the signal.

A.empirical mode decomposition

The Empirical mode decomposition method (EMD) proposed in 1998, is a self-adaptive data driven method, which decomposes a complex signal into a number of simple oscillatory modes called intrinsic mode functions (IMFs) [6].

These IMFs are determined by the signal itself rather than by pre-determined functions and designated by the following definitions:

1) In the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one.

2) At any point, the mean value of the envelopes defined by local maxima and the envelope defined by the local minima is zero.

The decomposition consists of the following steps [9]:

1) To identify all the local extrema, and then connect all the local maxima by an interpolation method to produce the upper envelope. Repeat the procedure for the local minima to produce the lower envelope.

2) To determine the difference between the signal $x(t)$ and m_1 which is the mean of upper and lower envelopes to obtain the first component, h_1.

$$x(t) - m_1 = h_1$$

3) To separate IMF (c_1) from the original signal $x(t)$ to obtain the residue r_1 :

$$r_1 = x(t) - c_1$$

4) To consider r_1 as the new data and repeat the above described process for n times, so that n-IMFs of signal $x(t)$ can be obtained. Then:

$$r_1 - c_2 = r_2$$

$$r_{n-1} - c_n = r_n$$

5) To stop the decomposition process when r_n becomes a monotonic function from which no more IMF can be extracted. By summing up Equations (4) and (5), we finally obtain:

$$x(t) = \sum_{i=1}^{n} c_i + r_n$$

B. Hilbert transform

Having obtained the IMFs using EMD method, the Hilbert transform is applied to each IMFs:

$$H[c_i(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{c_i(t)}{t-\tau} d\tau$$

Then, analytical signal is constructed as:

$$z_i(t) = c_i(t) + jH[c_i(t)]$$

Finally, the Hilbert-Huang transform and the Hilbert energy spectrum are represented, respectively as follows:

$$TFR_x(t,f) = \mathrm{Re}\left\{\sum_{i=1}^{n} a_i(t)\exp\left(j\int 2\pi f_i(t)dt\right)\right\}$$

$$TFR_x(t,f) = \sum_{i=1}^{n} a_i^2(t)\delta[f - f_i(t)]$$

where $\delta(\cdot)$ is the Dirac delta function.

These two steps, EMD and Hilbert transform allow obtaining three dimensions (time, frequency and amplitude) representation of the signal.

The EMD characteristic of being an adaptive band-pass filter bank with the bandwidth self-adaptively determined by the signal decomposed; whereas the filter features of wavelet decomposition is not self-adaptive.

III. TEAGER-HUANG TRANSFORM: THT

The Teager-Kaiser energy operator (TKEO), which is a nonlinear differential operator can estimate the energy required to generate a signal [9]. The TKEO is defined for a continuous time signal $x(t)$ as:

$$\Psi[x(t)] = [\dot{x}(t)]^2 - x(t)\ddot{x}(t)$$

où : $\dot{x}(t)$ is the first time derivatives of x(t).
$\ddot{x}(t)$ is the second time derivatives of x(t).

For a discrete time signal $x(n)$ (where n is the discrete time index), using difference to approximate differential, the TKEO can be proposed as:

$$\Psi(x[n]) = x^2[n] - x[n+1]\cdot x[n-1]$$

As at any instant, only three consecutive samples are needed to estimate the instantaneous TKEO, it is adaptive to the instantaneous changes in signals and is quite adapt to resolve transient events. It is an adaptive method and effective in estimating the instantaneous frequency and envelope amplitude of non-stationary signals. It has some merits such as low computational cost, high resolution of time and frequency and adaptability to instantaneous feature [10].

The instantaneous frequency and instantaneous amplitude at any time instant of the signal $x(t)$ can be given as:

$$F(n) = \frac{1}{2}\arccos\left(1 - \frac{\Psi[x(n+1) - x(n-1)]}{2\Psi[x(n)]}\right),$$

$$A(n) \approx \frac{2\Psi[x(n)]}{\sqrt{\Psi[x(n+1) - x(n-1)]}}$$

IV. EXPERIMENT RESULTS

A. Vibration data

The vibration data that were used for analysis are obtained from the Case Western Reserve University Bearing Data Center [16]. Reliance Electric's 2-hp motor, along with a torque transducer, a dynamometer, and control electronics, constitutes the test setup.

Figure 3 presents the waveforms of the vibration signals from the four bearing states.

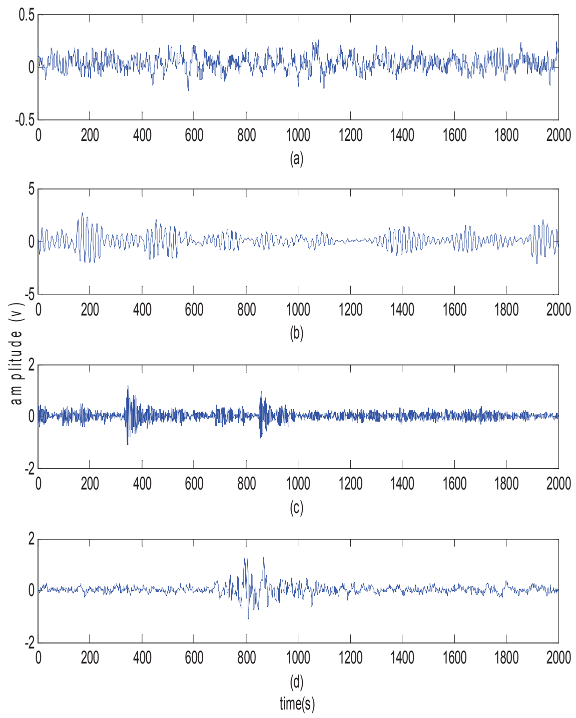

Fig. 1. Vibration signals

B. Empirical mode decomposition

The Hilbert-Huang transform is a time-frequency decomposition technique particularly suitable for the analysis of nonstationary vibration signals. 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-Huang transform. The empirical mode decomposition of the Vibration signals from the four bearing states: (normal, rolling element defect, inner race defect and outer race defect) are given in figures 2, 3,4and5.

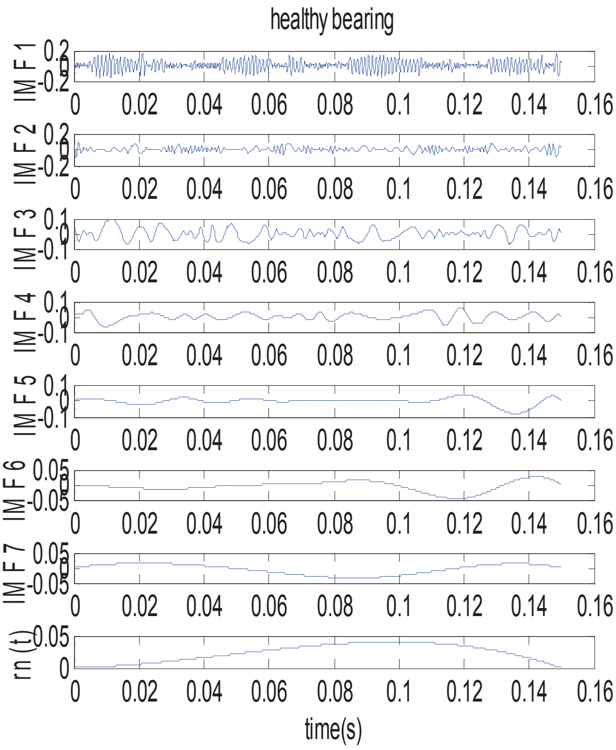

Fig 2. Empirical mode decomposition of the healthy bearing signal $x(t)$

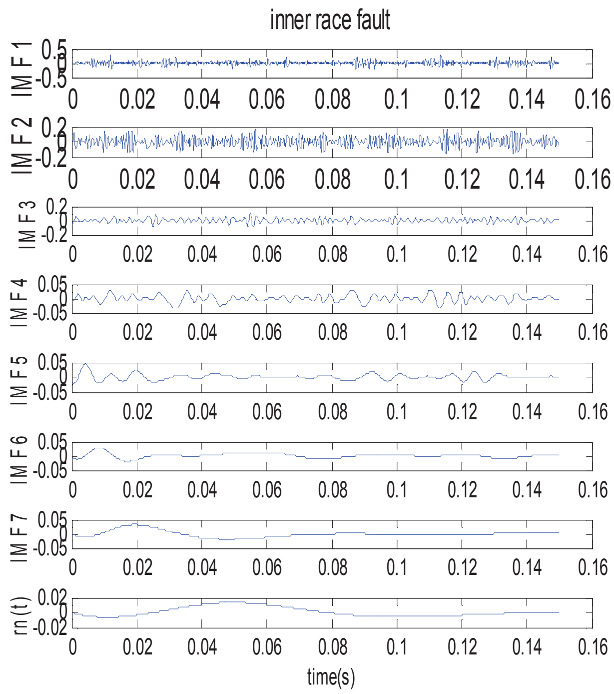

Fig 3. Empirical mode decomposition of the signal of rolling element fault .

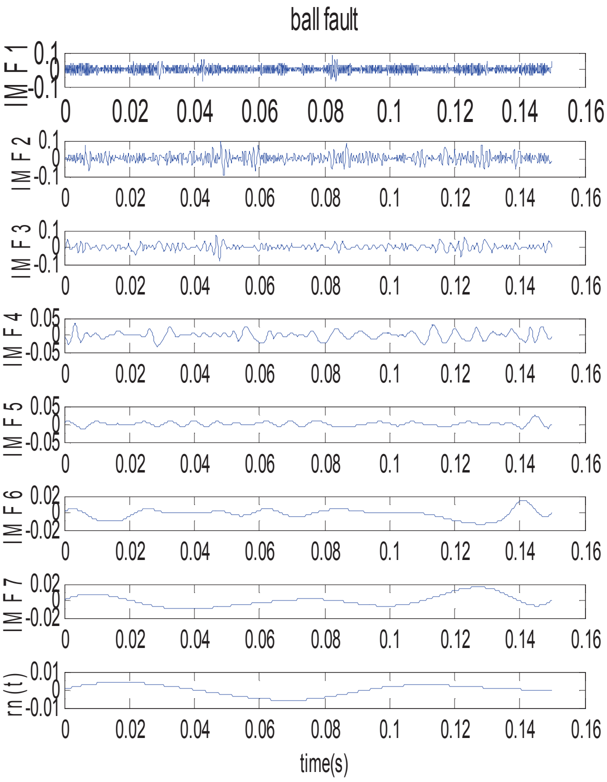

Fig.4. Empirical mode decomposition of the signal of inner race fault .

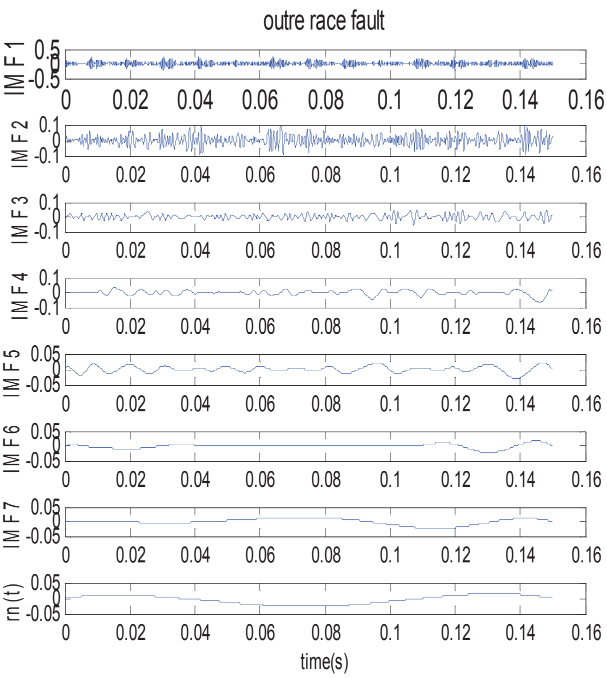

Fig.5. Empirical mode decomposition of the signal of outer race fault .

C. Hilbert marginal spectrum

The Hilbert marginal spectrum on the two first IMFs of the vibration signals from the four bearing states: (normal, rolling element defect, inner race defect and outer race defect) is used to separate the high frequencies of the low frequencies. In fact, from the figures 6, 7, 8 and 9, one can see that the Hilbert marginal spectrum applied to the first IMF identifies the high frequency components.

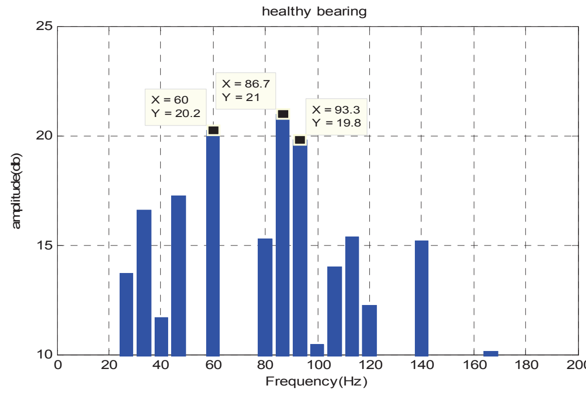

Fig.6. Hilbert marginal spectrum of the first IMF of healthy bearing signal

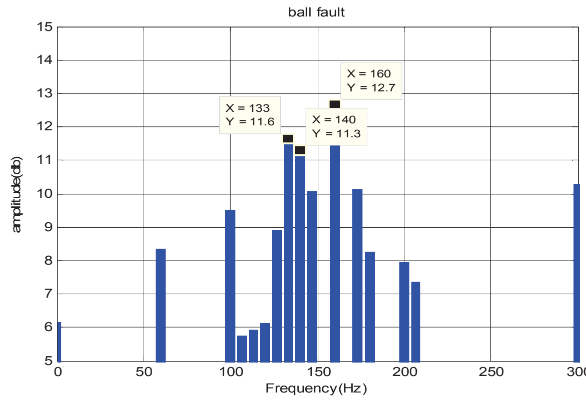

Fig. 7. Hilbert marginal spectrum of the first IMF of rolling element fault

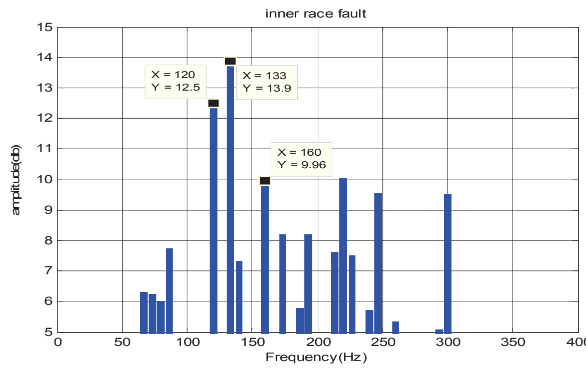

Fig. 8 . Hilbert marginal spectrum of the first IMF

of the inner race fault

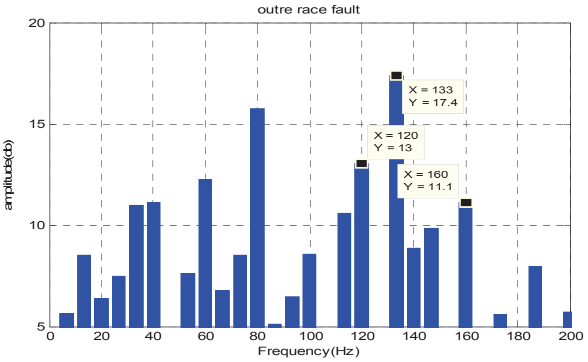

Fig. 9.. Hilbert marginal spectrum of the first IMF of outer race fault

These results show the effectiveness of the Hilbert Huang transform to track the amplitudes of the transient components.

D. Teager-Kaiser energy operator

The feature extraction phase is carried out by using the Teager-Kaiser energy operator (TKEO). The figures.10, 11, 12 and 13 present the envelope and Instantaneous frequency estimated by TKEO for vibration signals from the four bearing states (normal, ball defect, inner race defect and outer race defect). The envelope of signals considered the vectors forms of each bearing case faults.

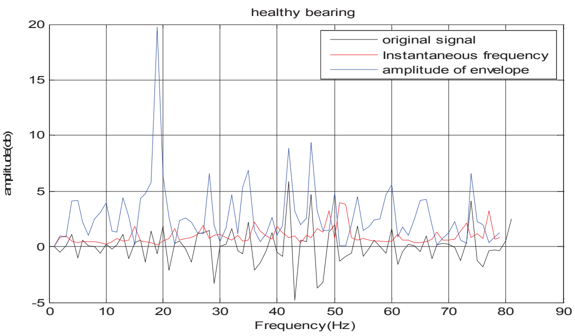

Fig.10. TKEO for healthy bearing

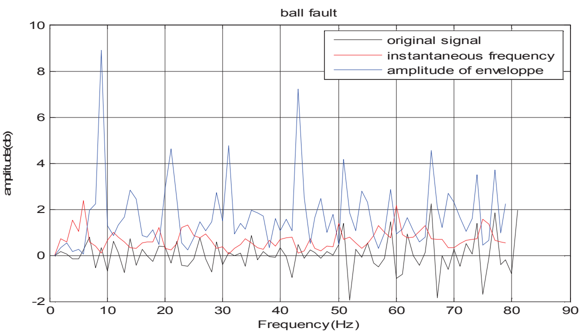

Fig. 11. TKEO of ball fault

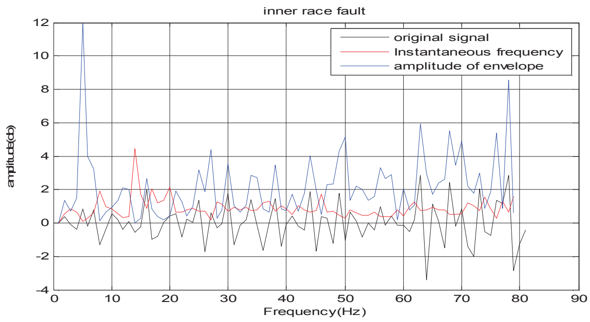

Fig.12. TKEO of inner race fault

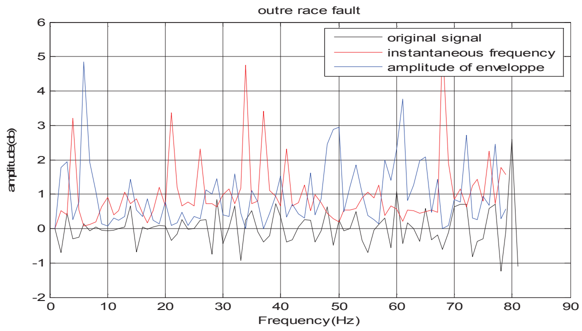

Fig. 14. TKEO of outer race fault

V. CONCLUSION

In this paper, We developed in approach based on Teager huang transformation (THT) to extract vectors forms of vibration signals for four bearing states (normal, rolling element defect, inner race defect and outer race defect) by use a Hilbert-Huang transform and Teager - Kaiser energy operator (TKEO). We are applied the Hilbert-Huang transform to decompose the signal into several IMFs. The Hilbert marginal spectrum applied which calculates the energy density at each frequency. We are using a Teager – Kaiser Energy Operator (TKEO) for extract vectors forms correspond a high energy density to the signals. To assess its computational efficiency in processing of feature extraction to the vibration signals. The results show the effectiveness of this approach for condition monitoring of bearings.

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