SIGNAL PROCESSING FOR FAULT DETECTION IN NON-STATIONERY AND NON- LINEAR MACHINES: A COMPARISON

[1]Sumit Kumar Sar, [2]Dr. Ramesh Kumar
[1]Assistant Professor. Scholar, [2]Professor
Department of Computer Science & Engineering
Bhilai Institute of technology, Durg

Abstract : Breakdown maintenance is no longer affordable for industries as we now understand that the losses incurred on procrastinating CBM and real time preventive maintenance are too painful to be continued with. Novel techniques of the age old vibration signature analysis are being developed, such as HHT which has several advantages over the traditional FFT as it does not require the machine to be constant in its movement. Neural networks can now be Deep - trained to identify faults precisely based on the above analysis. Incorporation and simultaneous analysis of real time data enables immediate decision making using Random Forest decision trees. An assembly of the above technologies makes a significant difference in the exactness of fault diagnosis of machines.

Keywords – Fast Fourier transform, Hilbert Haung transform, Non-Stationary Machines

I. INTRODUCTION

Human race is still dependent to a large extent on the vibration and sound of machines for fault diagnosis. Today, biological sensors and neural network has being replaced by man-made ones, to precisely point out fault, its reason and cure. This process of replacement, although never fully possible, needs continuous efforts to become seamless. Fast Fourier Transform has been used for the purpose for processing the obtained vibration signals of machines under study i.e. for extracting frequency information from time series data till recently. But the most significant consideration for FFT is that the machine has to be majorly stationery and linear, which is not the case in real world. Several factors such as wear and tear, gravitational variation, etc. affect the motion of the moving part of machines. Moving machines are a different cases all together [1]. Vibration signals of such machines cannot be efficiently processed by FFT. A more recent development in this area is Hilbert-Haung Transform, which generates amplitude as well as frequency from the time spectra. The HHT does not require the assumptions of stationarity and linearity of the data as required by FFT, and thus, is more adaptive.

Learning techniques of neural networks differ mainly in the explicity of the data used for training the diagnostic layers. This is a major consideration when it comes to utilizing the algorithm in real world conditions. Random Forest Decision Tree is a technique, in which the network can be trained to classify input data as per requirement. This prognosis makes the final output to be precise and accurate. Thus, faults can be identified and prevented in the true sense, thereby avoiding huge maintenance losses.

II. SIGNAL PROCESSING : TRADITIONAL FFT VS. EMD BASED HHT

1. The fast Fourier transform (FFT) was being used as an effective algorithm to obtain frequency based parameters from the time spectrum. Characteristically, the data to be transformed consists of N uniformly spaced points $x_q = x(t_q)$ where $N = 2^n$ with n is an integer, and $t_q = q\Delta t$ where q ranges from 0 to $N-1$. The DFT can be expressed in many different ways such as:

$$X_k = \sum_{q=0}^{N-1} x_q e^{(-2i\pi qk)/N} \quad (1)$$

Where $i = \sqrt{-1}$, $k = 0 \ldots N-1$ and x_q represent the time domain data and X_k their representation in the frequency domain. The algorithms for the FFT conversion process make it popular as it cuts down the number of computations, which understandably reduces the execution time. The frequency data are characteristically expressed as an amplitude spectrum or a power spectrum [2]. The amplitude spectrum is characteristically expressed as :

$$amp_k = \frac{2}{N}|X_k| \quad (2)$$

whereas the power spectrum is typically expressed by the relation

$$PS_k = \frac{1}{N}\left|X_k^2\right| \quad (3)$$

Where $k = 0,1,...,N/2$

2. The Hilbert-Huang transform process consists of two parts:

i) The empirical mode decomposition (EMD) - which decomposes the discrete sample signal into intrinsic mode functions (IMF) having two vital properties: 1) the number of extrema and the number of zero crossings which may differ only by one and 2) the mean value of envelopes defined by the local maxima and local minima is zero. Functions from FFT are harmonic, whereas these oscillatory functions vary in both amplitude and frequency in the given time. Typically the first IMF consists of the highest frequencies from the original signal and each subsequent IMF has lower-frequency components [3].

ii) The derivation of frequency parameter data from IMF's using Hilbert transform (HT) - Amplitude and frequency data is derived from the IMF's in the second part of the HHT. The computation of the HT is basically a convolution of an IMF, y(t), with 1/t. The effect of this process is to purify the parametric properties of y(t). This purification retains the time structure of the signal's amplitude and frequency. If we take a discretely sampled signal s(t), then the HHT process is as follows:

i. Define the location of all maxima, smax(t), and minima smin(t).
ii. Plot a Cubic spline through the smax(t) and another through the smin(t).
iii. Calculate the mean of the spline curves at each point
    a. mean(t) = (smax(t) + smin(t))/2
iv. Eliminate mean(t). Let d(t) = s(t) − mean(t).
v. If d(t) fulfils the conditions of an IMF, then
    a. let ci(t) = d(t) and increment i by 1.
    b. Extract the residual r(t) = s(t)×d(t).
vi. If d(t) doesn't fulfils the conditions of an IMF, further processing is required.
vii. Repeat steps 1 to 5, substituting d(t) for s(t).

We have to repeat steps 1 to 5 until the residual does not contain any useful frequency information any more. The sum total of the parts will, obviously, be equal to the original. If we have N number of IMFs and a final residual

$rd_N(\mathrm{t})$, then

$$s(t) = \sum_{j=1}^{N} c_j(t) + rd_N(\mathrm{t}) \quad (4)$$

The next stage of the HHT process extracts the amplitude and frequency information from every discrete IMF whose steps are as follows:

a) Calculate the IMF's discrete Fourier transform (DFT) using the equation (1) for the transform.

b) Calculate the HT. Use the real and imaginary parts of step 1's DFT as coefficients (M = N/2):

$$b_l = \frac{1}{N}\sum_{j1=0}^{M}\left(R(\mathrm{X}_{j1}\sin(2\pi j1\frac{l}{N})) + I(\mathrm{X}_{j1}\cos(2\pi j1\frac{l}{N}))\right)$$
$$+\left(\frac{-1}{N}\right)\sum_{j2=M+1}^{N-1}\left(R(\mathrm{X}_{j2}\sin(2\pi j2\frac{l}{N})) + I(\mathrm{X}_{j2}\cos(2\pi j2\frac{l}{N}))\right) \quad (5)$$

We then construct the complex number $c_l = a_l + ib_l$ and extract the phase $\phi_l = \tan^{-1}(\frac{b_l}{a_l})$.

Simplification of the phase makes it a monotonically increasing function. We then calculate the frequency and derivative of the phase

$$fq_l = \frac{1}{2\pi}\frac{d\phi_l}{dt}$$

Next, we calculate the amplitude.

$$amp_l = \sqrt{a_l^2 + b_l^2}$$

III. CASE STUDY OF BEARING IN AIR COMPRESSOR

Bearings, are important rolling components very commonly used in rotating machine parts. For this same reason, fault detection in bearings must be done as early and as precisely as possible, to altogether prevent fatal breakdowns of machines in order to avoid loss of production and human casualties. Commonly occurring faults in rolling bearings are defects in the outer-race, the inner-race, the rollers, or the frame. These faults create impact vibrations each time a rolling bearing passes over the surfaces of the defects. For different fault types, the vibrations will be of different frequency. In the initial experiments, Fast Fourier Transform/ analysis was the most common signal analysis tool for detection of bearing fault. But, there were found to be crucial restrictions of the Fast Fourier Transform: the signal under analysis has to be strictly periodic and stationary. Else, the resulting Fourier spectrum will be useless. This condition is almost never possible, as bearing vibration signals are always non - stationary and non - linear, and the frequency parameters change over time. Thus, the Fourier transform fails at this.

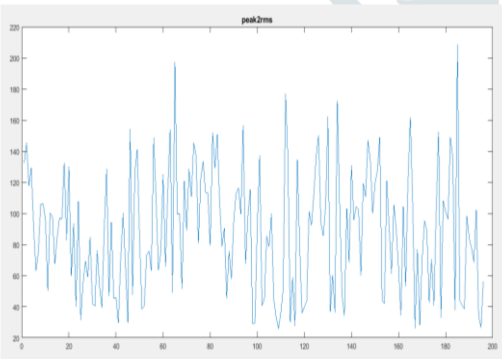
Later it was observed that, the time–frequency analysis methods generated both time and frequency information of a signal simultaneously through mapping the one-dimensional signal to a two-dimensional time–frequency plane. In the last few years, a time–frequency analysis method named Hilbert–Huang transform (HHT) has become a favorite [4]. HHT performs a time adaptive decomposition operation named empirical mode decomposition (EMD) on the signal; and decomposing the signal into a set of complete components named intrinsic mode function (IMF), which is almost mono - component. Applying HHT on those IMFs, we arrive at a full energy–frequency–time distribution of the signal, named as the Hilbert–Huang spectrum. The best part of HHT is that its most computation intensive step, the EMD operation, does not consist of time-consuming operations such as convolutions, which is why HHT can handle signals of in enormous amounts[5].

Next, in Hilbert–Huang spectrum instead of frequency resolution and the time resolution, there is the concept of instantaneous frequency. HHT may have the potential of becoming a perfect tool for non-linear and non-stationary fault detection. But, the HHT also has some problems, mostly caused by the EMD. Firstly, the EMD will generate some low amplitude IMFs at the low-frequency region and raise some frequency components which are not needed. This is the result of the noise generated by the bearing rolling over the defect every time. Secondly, the first IMF may cover a wide frequency range at the high-frequency region and thus will not satisfy the mono-component definition. Thirdly, the EMD operation often cannot distinguish few low-energy components from the under-analysis signal, thus those components may not appear in the frequency–time dimension [6].

Thus, HHT has a scope for improvement for becoming a preferred tool for signal analysis of non-stationary and non-linear vibrations [7]. This idea may be explored in later studies. As of now, we have found that, HHT gives a more precise analysis result than FFT[8], and is thus being used for our study.

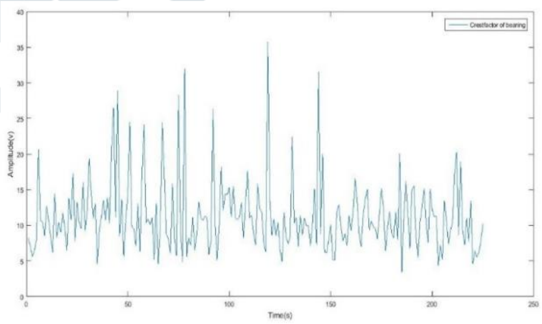
Below, we have put results of our analysis of rolling bearing faulty vibration signal using both FFT and HHT[9]. Parameters that have been studied are Kurtosis, RMS and Crest factor. We have developed a code in MATLAB for analysis of a rolling bearing data set and have compared the results of both analysis tools, to conclude that HHT treats the signal under analysis in a more detailed manner.

FFT Results

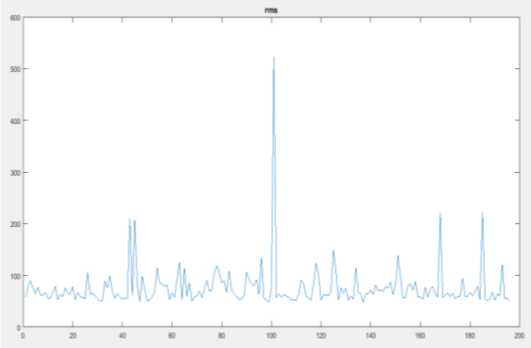


Crest factor

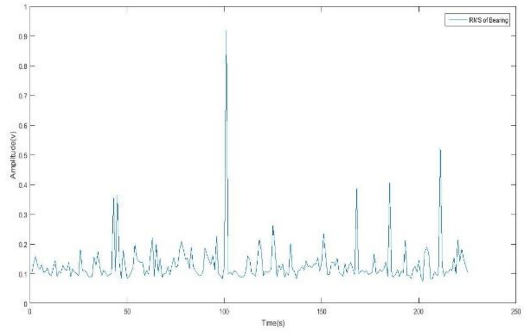
HHT Results



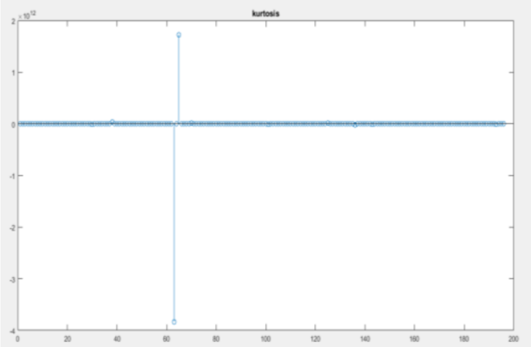
Crest factor



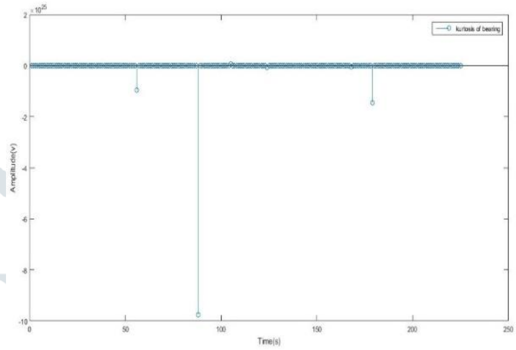
RMS



RMS



Kurtosis



Kurtosis

3.1. Computation time

Table 1: Computation time of proposed HHT transform and existing FFT Transform

Sl. No.	Algorithm	Run Time
1	Fast flourier Transform	0.013
2	Hilbert Haung Transform	0.021

The above table presents the average computation time for computing each transform and its corresponding parameters. These values were found by averaging the computation time over 1000 recordings, which describe the computation time of both FFT and HHT[10][11]. Computation time of HHT is found to be very marginally higher, due to the 2 highly computation intensive stages involved in the system. But, the parameters extracted from the vibration signal are more precise and mono-component.

V. CONCLUSION

On comparing FFT with HHT for analysis of vibration signals of machines which have rolling components, it was found that HHT took into consideration factors that were being overlooked by FFT. Any machine having developed a defect in its structure is bound not to be perfect in its motion. Noise generated due to every impact at the defect site has to be eliminated and analysis has to be suitably done. Also, such a structural defect renders the motion of the rolling component of the machine mis-aligned with rest of the machine. This consideration of non-linearity and non-stationarity was missing with FFT.

The results of the MATLAB codes using FFT and HHT respectively, for signal analysis and parameter identification verify our above observation as can be seen from the graphs above.

Thus, we conclude that for such an analysis of vibration signals for the purpose of fault detection and prediction of defects, HHT is a better tool than the currently preferred FFT [12]. Our earlier assumption of implementing FFT for our Fault diagnosis vibration signature analysis will now be better and more precise as HHT will now be used for the same.

It may be safely assumed that the short comings of HHT will be removed in future and an improved version of the same will be developed for the purpose of signal analysis, which will lead to a much needed improvement in condition-based monitoring of our systems and machines.

V. ACKNOWLEDGMENT

This work is supported by Department of Computer Science and Engineering, Bhilai Institute of Technology, Durg and Dr. Ramesh Kumar. We also thank IIT Kanpur for making data sets of various machines available for research and study.

REFERENCES

[1] Norden E. Huang et. al., 1998 "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis,", Proc. R. Soc. Lond. A., vol. 454, pp. 903-995.

[2] Denis Donnelly, 2006 , "The Fast Fourier and Hilbert-Huang Transforms: A Comparison", International Journal of Computers, Communications & Control, Vol. I, No. 4, pp. 45-52.

[3] Arnab Roy and John F. Doherty,2008, "Empirical Mode Decomposition Frequency Resolution Improvement using the Pre-emphasis and De-emphasis Method", 42nd Annual Conference on Information Sciences and Systems (IEEE), pp 453-457.

[4] Z K Peng et. al., 2005, "A comparison study of improved Hilbert–Huang transform and wavelet transform: Application to fault diagnosis for rolling bearing", Mechanical Systems and Signal Processing (Elsevier), vol.19, issue 5, pp 974-988.

[5] N.E. Huang, Z. Shen, S.R. Long, 1999, "A new view of nonlinear water waves: the Hilbert spectrum", Annual Review of Fluid Mechanics 31, pp 417–457.

[6] M.E. Montesinos, J.L. Munoz-Cobo, C. Perez, 2003, "Hilbert–Huang analysis of BWR neutron detector signals: application to DR calculation and to corrupted signal analysis", Annals of Nuclear Energy 30, pp 715–727.

[7] Peng Li et. al, 2011, "Based on the Improved HHT and Its Application in the Power Quality Detection of Microgrid", International Conference on Electrical Machines and Systems IEEE, 20-23 Aug. 2011.

[8] K. Rasool Reddy et. al., 2015, "Analysis of Non stationary Data signals Using Hilbert Haung Transform", International Conference on Computational Intelligence and Communication Networks, pp 502-507

[9] Issam Attoui, et al., 2015, "Vibration-based bearing fault diagnosis by an integrated DWT-FFT approach and an adaptive neuro-fuzzy inference system ", International Conference on Computational Intelligence and Communication Networks (CICN).

[10] https://in.mathworks.com/matlabcentral/fileexchange/37545-envelope-detction-for-signal-analysis.

[11] https://in.mathworks.com/matlabcentral/fileexchange/37226-imf-for-bearing-fault-diagnosis.

[12] Pratik Rajendra Manve1, Raja Narasimha S., 2017, "Condition monitoring and fault identification of new deep groove ball bearing using LabVIEW", Journal of Emerging Technologies and Innovative Research (JETIR), vol. 4, issue 2, pp 104-108.