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Application of Empirical Mode Decomposition for Tool Wear Monitoring using Vibration Measurement

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***Abstract*—Tool wear monitoring requires excellent capabilities of detecting small defects within the item under test. Diverse techniques have been using to detect the effect of vibrations on a tool, hence on material. The paper presents an EMD (empirical mode decomposition) approach for point out the effect of vibrations for a tool under machining in industrial process. EMD exhibits good results in processing some signals and simplicity in its use.**

***Keyswords*— Empirical mode decomposition, signal processing, vibration measurement, environmental measurements.**

1. INTRODUCTION

Material removal machining remains most important manufacturing process and is used most in mechanical industry in a wide range of aerospace applications to the automotive industry. The state of tool and its service life are critical to machining cost. Use of a vibration generating machine depends on quality of surface condition, dimensional accuracy of machined parts, and production time.

Fig.1. An example of item under machining

Monitoring tool wear is a more complex task. Many papers have been proposed to use different types of signals resulting from machining, such as: cutting forces, emission acoustics and vibrations, and have proved their effectiveness and their ability to monitor the wear of tools. Work using signal processing techniques was conducted by Ramili et al [1]. focuses on the treatment of the vibratory signature by machining. The ranking and prediction of the state of the tool with the input data of one or more sensors and network architectures of neurons have been studied. The wavelet transform is considered as one of the best. However, the wavelet transform still has some unavoidable shortcomings, including the terms of interference, distortion of the border and energy leakage, all of which will generate a lot of small unwanted spikes throughout the frequency scales and make the results confusing and difficult to interpret. Therefore, new methods are needed to analysis the data from non-linear and non-stationary processes such as drilling, turning, etc. In 1998 a new frequency-time method called empirical mode decomposition (EMD) was proposed by Huang [2]. Monitoring of wear of cutting tool during these three phases of life. This analysis aims to demonstrate if there is a relationship between evolution of wear and measured quantities (vibrations) during machining and extract the relevant indicators. Fig.1 shows the trend of failure rate along the time.

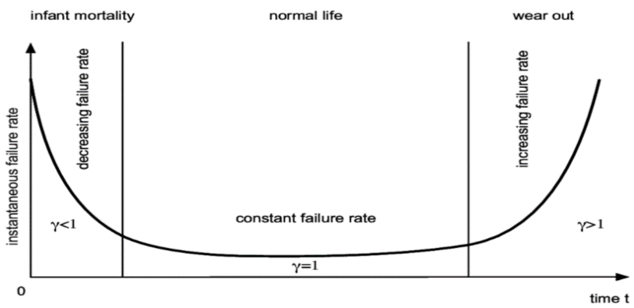

Fig.2. Bathtub curve for failure analysis

Instead, damages are caused by three factors: (i) abrasion which is subsequent to the removal of material on the tool by hard constituents in the machined material; (ii) adhesion, this wear is also caused by the tearing of particles using a tool, after micro strain in the chip and in the tool; (iii) broadcast: the broadcast wear automatically appears. Fig.2 depicts the damage mechanism that certainly influences the cutting tool operating mode. The life of the cutting tool is mainly constrained by the development of three types of wear: flank wear, crater wear and nose wear.

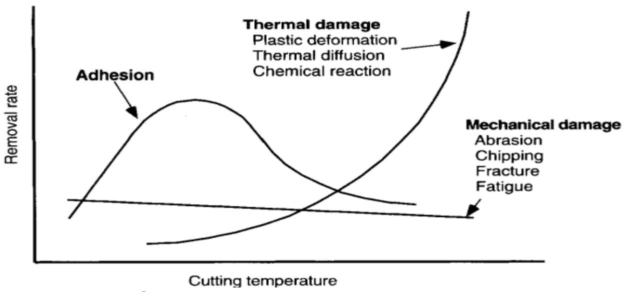

Fig.2. Damage mechanism

Flank is a friction between side of cutting-tool edge and metal being machined. Crater wear takes place as a consequence of chips sliding along chip-tool interface. Nose wear is caused by friction between nose and metal being machined. According to ISO 8688 [3], the tool life is defined as:" the total cutting time of the tool to reach a specified value of life criterion". The flank wear, under normal machining conditions, is considered to be predominant wear. Following ISO 3685 [4] and NF E 66-505 [5], the accepted wear width, called V_b, is equal to 0.3 mm. If no, the allowable limit 0.6 mm. For the scope of this work the have set the limit at 0.3 mm.

2. EMPIRICAL MODE DECOMPOSITION

Empirical Mode Decomposition (EMD) has been introduced by Huang et al. [6] to nonlinear and non-stationary time series. Like Wavelet Analysis, EMD attempts to decompose a time series into individual components (intrinsic oscillations) by exploiting both local temporal and structural characteristics of the data. EMD achieved through a linear sum of the components that approximates the original ECG signal. In this work, EMD on univariate time series has been examined. However, recently, a multivariate version of the EMD (MEMD) has been successfully proposed [7]. The starting point of EMD is to locally estimate a signal as a sum of a local trend and a detail signal component: the local trend is a low frequency part, and the local detail accounts for high frequencies. In EMD, the high-frequency (detail) components are referred to as Intrinsic Mode Function (IMF) and the low frequency part is called residual. The procedure is then applied again to the residual, considered as a new times series, extracting a new IMF and a new residual.

Table I Comparison among different techniques

	Fourier	STFT	Wavelet	HHT (EMD)
Basis	Non-adaptive	Non-adaptive	Non-adaptive	Adaptive
Frequency	Convolution: Global	Convolution: Regional	Convolution: Regional	Differentiation: Local
Presentation	Energy – frequency	Energy –time - frequency	Energy-time-frequency	Energy-time-frequency
Nonlinear	No	No	No	Yes
Non stationary	No	No	Yes	Yes
Feature Extraction	No	Discrete: No Continuous: Yes	Discrete: No Continuous: Yes	Yes

EMD is not the only technique that can be used for activities of this research. Table I illustrates an EMD comparison with other techniques used for monitoring tool wear; Fourier and STFT belong to the same category as transforms to be used in many applications with no high complications. Wavelet is also interesting since it can allows to overcome some general limitations of Fourier and STFT in the cases of specific applications.

3. EXPERIMENTATION AND ALGORITHM

The machining tests were carried out at the mechanical workshop ISTA on a classic HYDROGALLIC brand lathe, it carries a two-speed Siemens motor with 10 HP power supplied, The material chosen is a hard steel, and the dimensions of the machined cylinder are 300 mm in length and 50 in diameter we have used the tools in plate and the monoblock in metal carbide.

Fig.3. Lathe used for experimental activities

A set of sensors is used (Fig.4); in particular, an accelerometer is fixed on the turret to measure the vibration responses in the cutting tool along the machine axis : The measurement of the accelerometer signals during machining was performed using an acquisition chain composed of a mono-axial piezoelectric accelerometer type and a National Instrument (NI) acquisition system including the Compact DAQ on which we mounted the 9233 module for the conditioning of these signals is controlled by the LabVIEW software which allowed us to program the acquisition interface, the sampling frequency was 25000 Hz, and the number of samples 250000 so we recorded responses generated during machining in its entirety.

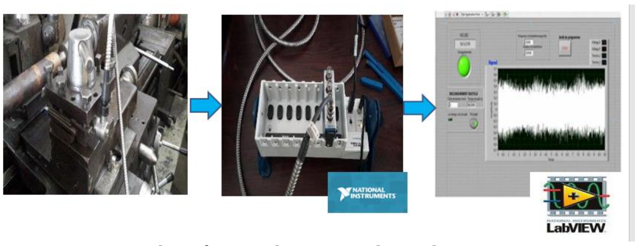

Fig.4. Acquisition chain from tool to acquired signal

The IMFs (Intrinsic Mode Function) are mathematically subject to two conditions:

a) in the whole data set, the number of extrema and zero crossing must be equal or differ at most by one;

b) at any point the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero.

The aforementioned conditions are empirical and there is no any explicit formula for estimating IMFs. Given the analysis of the power spectrum of IMFs, as it will be shown, it is possible to verify that these functions represent the original signal decomposed into different time-scales or frequency bandwidths. Given a signal $x(t)$, the general algorithm of EMD can be summarized as follows [8]:

1. identify all extrema (minima and maxima) of $x(t)$;
2. generate the upper and lower envelope ($e_{min}(t)$, $e_{max}(t)$) by connecting the maxima and minima points separately with cubic spline;
3. compute the local mean $r(t) = (e_{min}(t) + e_{max}(t))/2$;
4. extract the detail $d(t) = x(t) - r(t)$;
5. iterate on the residual $r(t)$.

At the end of the decomposition process, the EMD method exhibits the signal $x(t)$ as the sum of a finite number of IMFs and a final residual [9]:

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

where $h_i(t)$ are the IMFs and $r_n(t)$ is a final residual, which is less than an arbitrarily chosen threshold. The algorithm works iteratively by identifying the extrema of the signal and breaking it down thus ensuring that the number of modes is finite. The envelope is estimated by interpolating the extrema of the signal at each iteration. The EMD algorithm needs to be focused on both the choice of the extrema, in order to avoid over-sampling issues, and the boundary conditions for the analysis of discrete time sequences. The effective algorithm used is this paper is illustrated in Fig.5.

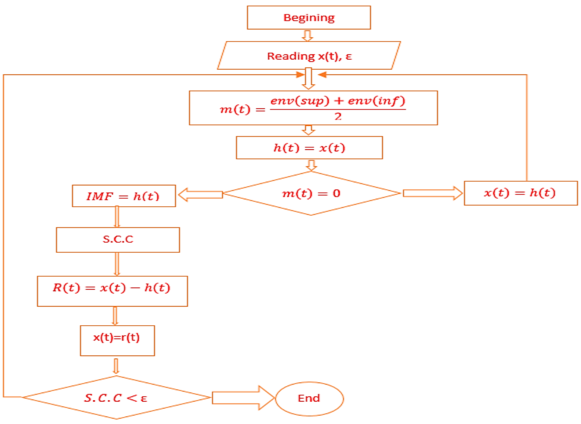

Fig.5. Proposed algorithm for EMD connected to wear detection

4. PRESENTATION OF RESULTS

The results below show the application of the algorithm to detect the tool wear in three specific cases in order to illustrate that EMD is a powerful algorithm in the field of signal processing. The three cases are the followings: new tool without wear, low tool wear, and high level-based tool wear. We start with the first case as a reference case of the same tool to be used in the other two. Fig.6 depicts 6 IMFs extracted from the signal processing along with the residue.

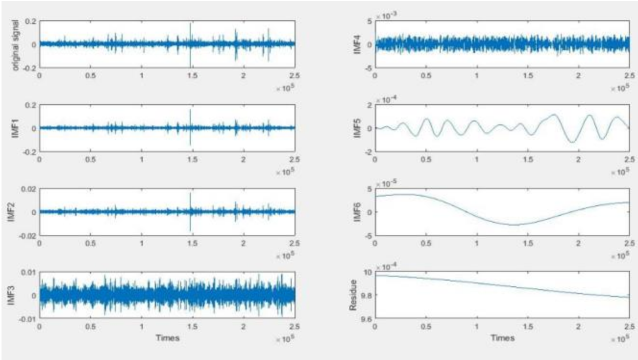

Fig.6. EMD application for new tool

Attention must be paid on the original signal, IMF1, and IMF2 at time set for 1.5. Their behavior is the same, no specific changes are observed. This is a first indication of material homogeneity, that means new tool without wear.

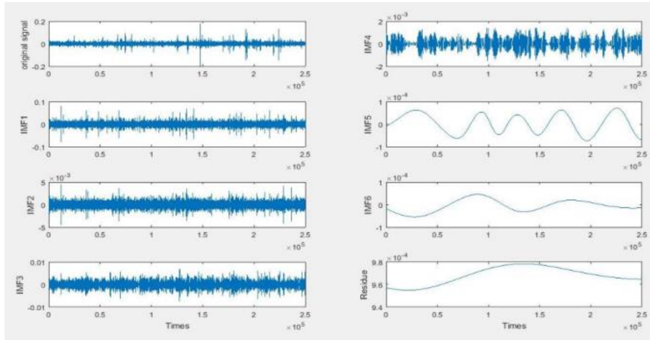

Fig. 7. EMD application for low tool wear

For low tool wear, according to Fig.7, the original feature, with peak at time set for 1.5, is not the same for IMF1, and IMF2. But the residue exhibits a maximum close to 1.5 as times. This is a typical behavior of low vibrations, then low tool wear. Moreover, the IMF4 shows more oscillations than the case of new tool without wear. Concerning the last case, high level-based tool wear, reported in Fig.8, beyond the reactions of IMF1, IMF2, we can see that IMF5 displays many oscillations than the previous two cases. It means that a major level of wear. The residue is totally different.

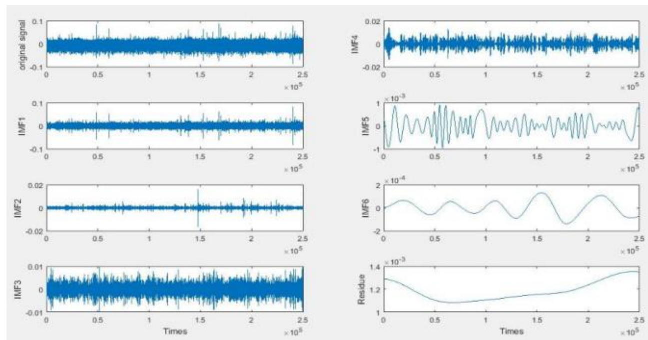

Fig. 8. EMD application for high level-based tool wear

The three examples show that different behaviors are encountered for each case, that is, no wear, low wear, and high wear. For each case, we get a specific signature in terms of oscillations, and residue.

5. CONCLUSION AND FINAL OUTLOOK

In this work, the relationship between the change in the amplitude of the tool delivering its signal and the side of the tool wear have been studied during the turning process with metal carbide piece. Signals emitted by vibratory tool for three different wear conditions of the side of the tool have been experimentally studied and analyzed using Hilbert-Huang Transform (HHT). It has been found that the magnitudes of some relevant IMF statistics issued tool components wear on the sidewalls of the tool decreases. The results of the survey confirm that HHT is based on sound signal analysis, and can be applied with confidence to monitor wear on the sidewall of the tool. Spectral estimate is a key approach insofar as any technique we have to adopt , as reported in Table 1, should take into account the concept of maxima and minima [10] [11]. The approach proposed can be included in CPS (cyber-physical system) vision [12] to be used in networking.

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