Experimental Study for Prediction of Tool Wear Using a Hybrid Method

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Abstract

In this paper a hybrid method based on the combination of Empirical Mode Decomposition (EMD) and Wavelet Multi-Resolution Analysis (WMRA) is proposed. The pairing of these two time frequency techniques is well adapted to analyze transient signals generated by the tool wear in the machining process. Indeed, the scalar indicators of energy and Mean powers are very sensitive to the variations in temporal signal related directly to the vibration induced during the turning operation. Nevertheless, their reliability is immediately limited by the presence of high levels of random noise. To ameliorate these deficiencies, by seeking help from the Wavelet Multi Resolution Analysis (WMRA) and a simple but effective method for intrinsic mode function (IMF) selection, a Hybrid system between WMRA and EMD is put forward as a solution to this problem. The results show that the proposed method (hybrid method) is superior to the WMRA or EMD alone.

Keywords: vibration signal, intrinsic mode function, wavelet multi-resolution analysis, tool wear

1 Introduction

Monitoring of tool wear is an important requirement for realizing automated manufacturing. Tool wear is a very complex phenomenon which can lead to machine down time, product rejects and can also cause problems to personnel [1]. Tool condition monitoring is a critical area for the success of any machining process where the tool is in constant or intermittent contact with the work-piece and can be subjected to continuous wear or catastrophic failure, fracture, etc. Therefore, the detection of tool wear is essential to improve manufacturing quality and to increase productivity. In most approaches, proposed for the tool wear monitoring area, several parameters can be measured, such as forces, vibration signal, and acoustic emission, which are directly correlated with tool wear. Furthermore, these parameters are measured on-line during the machining process [2-5]. Several studies have focused their efforts on the detection of tool breakage. The effect of tool breakage is usually revealed through an abrupt change in the processed measurements. Similar work conducted by Rmili and colleagues [6] concentrates on treating the vibratory signature generated by machining. The adopted strategy is based on a temporal analysis or statistical parameters. Then, in the frequency domain using the spectrogram method and smoothed averages. Coming address limits of the spectral analysis, wavelet analysis to enable a local signal unlike spectral analysis rather that it allows an overall view. Several applications of wavelet analysis have been proposed, in its continuous and discrete version [7].The classification and prediction of the tool state with input data from one or more sensors and architectures of neural networks [8-9]. Generally, some methods have been applied successfully, such as pattern recognition, wavelet transforms and so on; however, the traditional method is not adaptive, nonlinear, and orthogonal. In the recent years, another analysis method named Hilbert–Huang transform [10-11] has become more and more popular. The technique works through performing a time adaptive decomposition operation named empirical mode decomposition (EMD) on the signal; and then the signal will be decomposed into a set of complete and almost orthogonal components named intrinsic mode function (IMF). In this article a hybrid method based on the combination of EMD and WMRA is proposed. The proposed method is then compared, in several configurations, to EMD and WMRA. It gives better results than the application of the mentioned techniques alone.

2 Lifespan of tool wear

The life of cutting tool represents the actual productive time during which the cutting edge is directly related to tool wear. The wear manifests on the cutting tool in several forms dependent cutting conditions, the material being machined, the material of the cutting tool and its geometry. In normal conditions, flank wear VB is considered to assess the predominant wear to evaluate the lifespan of the cutting tool [12]. Different models of the wear laws have been established, Taylor was the first researcher who proposed in 1907 a mathematical model relating the effective cutting duration (lifetime) of the tool to the cutting parameters. Currently, the simple model of Taylor is sufficiently representative; it is usually used today for all materials of tools [13]. In practice, and also theoretically, the flank wear VB follows the pattern represented by Figure 1 and presents three wear phases: break-in (A), stabilization of wear (B) and accelerated wear (C).

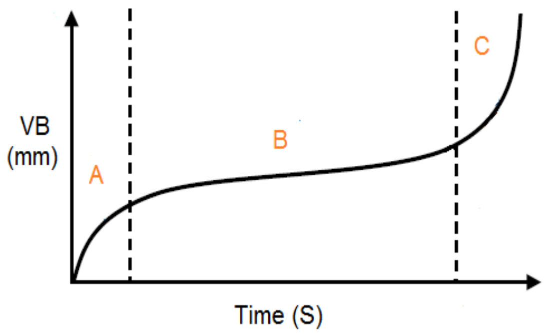

Figure 1: Theoretical tool wear

In the present work, we are interested in measuring the acceleration signals to predict the state of wear process in turning operation. For this purpose, we used based on EMD and WMRO.

3 Empirical mode decomposition theory

The EMD is defined by a process called screening (sifting) to decompose the signal in core contributions called empirical methods or IMF (Intrinsic mode functions). Decomposition is local, iterative, sequential and entirely data-driven. The primary objective of the EMD is to extract a non-stationary signal from systems that can be non-linear patterns that lend themselves to a time-frequency analysis; where Fourier analysis and wavelets are sometimes ineffective. It indeed makes the time-frequency representation more readable and clean physical interpretation. The principle of the EMD decomposition is provided by the screening process set by the algorithm described in the following. The Figure 2 shows the principle of EMD (decomposition of signals in different modes: IMFs). The IMFs is an innovation proposed by Huang design and colleagues [14] in the empirical mode decomposition, which is defined as a function which satisfies the following steps:

(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 envelope defined by local maxima and the envelope defined by the local minima is zero;

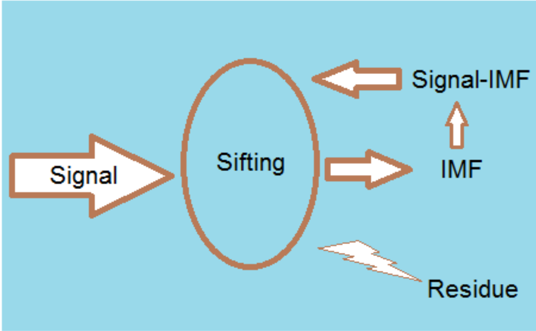

Figure 2: Principle of empirical mode decomposition

The EMD algorithm of a signal s(t) contains four steps:

1. Initialize: r_0=s(t), and i=1
2. Extract the ith IMF (c_i)
   (a). Initialize: $h_{i(k-1)}=r_{i-1}$, k=1
   (b). Extract the local maxima and minima of $h_{i(k-1)}$
   (c). Interpolate the local maxima and the minima by cubic spline lines from upper and lower envelopes of $h_{i(k-1)}$
   (d). Calculate the mean $m_{i(k-1)}$ of the upper and the lower envelopes of $h_{i(k-1)}$
   (e). Let $h_{ik}= h_{i(k-1)}- m_{i(k-1)}$
   (f). If h_{ik} is an IMF then set $c_i= h_{ik}$, else go to step (b) with k=k+1
3. Define the remainder $r_{i+1}=r_i-c_i$
4. If r_{i+1} still has least 2 extrema then go to step (2) with i=i+1 else the decomposition process is finished and r_{i+1} is the residue of the signal.

The decomposition method is applied empirical mode measures the signals. This application has a decomposition given several IMFs.

4 Wavelet multi-resolution analysis theory

The wavelet transform is a mathematical transformation which represents a signal s(t) in term of shifted and dilated version of singular function called wavelet mother ψ(t). The family of wavelets has the form:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

With *a* and *b* the scale and the translation parameters, respectively. Noting by $\psi^*(t)$ the conjugate of ψ(t), the Continuous Wavelet Transform (CWT) of the signal s(t) is defined by:

$$CWT(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} s(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{2}$$

The Discrete Wavelet Transform (DWT) is a discretization of the CWT. By replacing *a* and *b* by 2^m and $n2^m$, respectively, the above expression becomes:

$$DWT(m,n) = 2^{\frac{-m}{2}}\int_{-\infty}^{+\infty} s(t)\psi^*(2^{-m}t-n)dt \tag{3}$$

With *m* and *n* integers.

A practical version of this transform, called Wavelet Multi-Resolution Analysis (WMRA), was introduced for the first time by Mallat in 1989. It consists to introduce the signal s(t) in low-pass (L) and high-pass (H) filters. In this level, two vectors will be obtained, cA_1 and cD_1. The elements of the vector cA_1 are called approximation coefficients, they correspond to the low frequencies of the signal, while the elements of the vector cD_1 are called detail coefficients and they correspond to the highest of them. The procedure can be repeated with the elements of the vector cA_1 and successively with each new vector cA_j obtained. The process of decomposition can be repeated n times, with n the number of levels. During the decomposition, the signal s(t) and vectors cA_j undergo a downsampling, this is why the approximation cA_j and detail cD_j coefficients pass through two new reconstruction filters (LR) and (HR). Two vectors result; A_j called approximations and D_j called details.

5 Experimental validation

5.1 Machining testing device

The lathe used for machining operations is TOS TRENCIN; model SN40C, spindle power 6.6KW. The specimens are made of high chromium grade X200Cr12 (AISI D3). This steel has excellent wear resistance, usually used for the production of dies and punches for cutting and stamping, profiling rollers, combs rolling nets. For testing, we machined specimens diameter Φ=80mm and length L=400mm. The cutting insert used is a coated carbide $TiCN/Al_2O_3/TiN$ removable, of square form with eight cutting edges. Cutting operations were conducted without applying cutting fluid, and all cutting tests were performed under the following cutting conditions: cutting speed = 175 m/min; feed rate = 0.12 mm/rev; and depth of cut = 0.20 mm. The acquisition of vibration signals, we used triaxial piezoelectric accelerometers, Brüel & Kjaer Type 4524B. The acceleration signals are acquired during periods of 169 seconds on the observation channels three (x, y, z), taken at 32768 hertz. Each signal contained 16,384 samples. Data collected were stored directly on the PC using the acquisition and analysis system controlled by Pulse shop Lab ® software developed by Brüel & Kjaer Pulse laboratory (Figure 3).

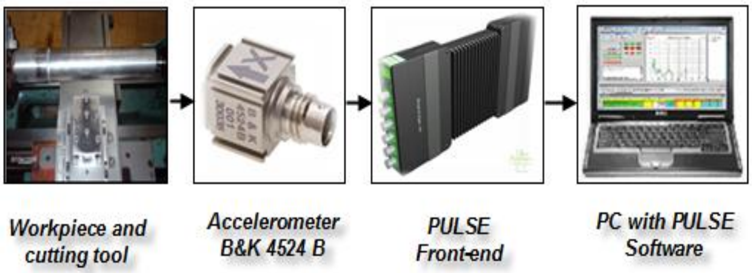

Figure 3: Device used to measure the vibration signals

The development of wear on the cutting insert is measured after each machining pass by an optical microscope type-Visual Standard guarantee 250 optical magnification of 0.7x to 4.5x actual size.

5.2 Answers vibration and evolution of flank wear VB

The machining tests were performed without lubrication when the stop flank wear (VB) reaches or exceeds the value of 0.3mm, which is synonymous with the life of the cutting insert. At this value, the insert is in the acceleration phase of wear corresponding to a critical zone of the machining quality.

Figure 4 shows an example of a concatenation of vibration acceleration signals over the entire service life of the cutting tool. According to these responses are observed that there are three main phases of the cutting tool life up period, stabilization of wear or flank wear increased uniformly and accelerated wear of where the tool wear rate increases until the rapid aging of the tool occurs. In particular, the transition to the acceleration phase of wear is certainly detectable in the direction (y).

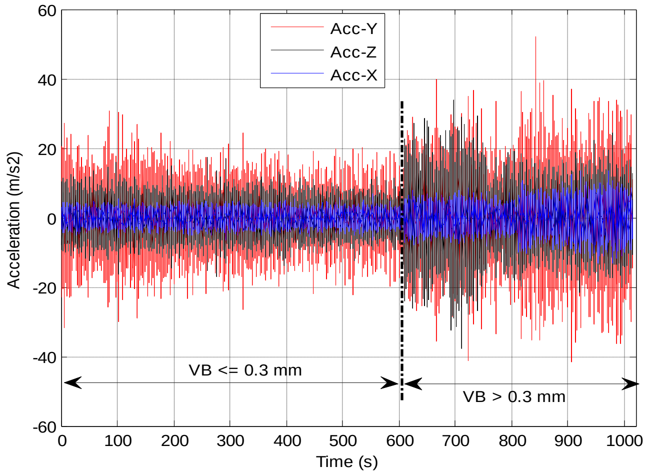

Figure 4: Evolution of flank wears according to the time of machining over all the lifespan of five vibratory answers

This observation is the same on all acquisitions. The analysis given tends to allow the detection of the transition region of the stabilization phase after the accelerated wear phase. The importance of determining this transition is fundamentally linked to the beginning of aging of the tool before the total collapse of the cutting.

6 Results and discussions

6.1 Optimal choise of the WMRA

Following this method we calculated the different scalar indicators based on different levels of detail. For comparison, it is noted that the optimum level wavelet resulting from the analysis of the component of acceleration is the highest, that is to say, the reconstructed signal (D1) is much clearer and more importantly which allows for a better result. This shows that the reconstructed signal provides a more reliable average power is very sensitive than the other indicators. In this application the noise and other components pollute the acquired signals and make monitoring difficult. The use of wavelet multiresolution analysis allows for the denoised and filtered with different scalar indicators is more significant signals. The results indicate that the scalar indicators had fewer significations and were found to be mostly insignificant. Naturally, in order to compare the results of the analysis, we conclude that the scalar indicators inspected (Energy and Mean powers) is less significant for this cutting speed 175 m/min.

The wavelet multiresolution analysis still cannot fulfil the Tool wear detection task very well since it has some inevitable deficiencies. To ameliorate these deficiencies, by seeking help from the the Empirical Mode Decomposition (EMD) and a simple but effective method for intrinsic mode function (IMF) selection.

6.2 Optimal choise of the EMD

The results of IMFs and the residue are illustrated in Figure 2, gives this signal's IMFs and the residue produced by the EMD. Obviously, only the first three IMFs are the real components of the signal and the others are the pseudo components that have low frequency and will be represented as low-frequency components. Observing the real IMF components will have relatively good correlation with the original signal. On the other hand, the pseudo components will only have a poor correlation with the signal.

To illustrate this signal together with its IMFs (IMF1, IMF2 and IMF3) and their respective FFT spectrums are given in Figure 5. Obviously, the IMF1 contains many frequency components and, on the other hand, the other IMF is almost monocomponent. Each IMFs shows a spectrum in a specific frequency band; According to the spectrum of IMF1, we distinguish the clean modes from the tool appearing in the frequency band between 4100 and 4800 Hz which identified by the modal analysis. In this context, one will be interested for the variations concerning the first three IMFs, classified as the most significant and that cover all the tool life.

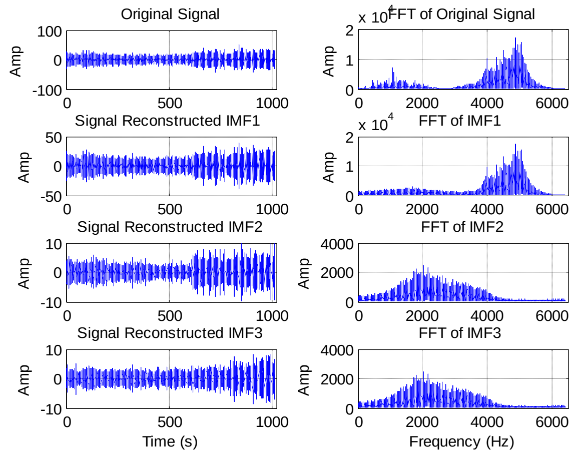

Figure 5: IMFs and their spectrums

The variation of the scalar indicators of the first three IMFs according to flank wear for the radial direction. We see that the variation of these indicators depending on the flank wear according to the radial direction is clearly detectable is better for IMF1. The Energy of reconstructed signal IMF1 passes from 7.062E+005 to 0.077 mm the flank wear in the running-in phase to 3.066E+005 in the stabilization wear phase for VB = 0.373 mm before decrease in the accelerated wear phase to 1.364E+006 for VB = 0.628 mm.

6.3 Approach proposed: Hybrid method

We chose to apply WMRA to the signal to be analysed like a pre-treatment, is to decompose the signal to some narrow band signals at first, and then use EMD operation on those narrow band signals, and thus the obtained IMFs will also have narrow frequency bands. The suggested approach is that the application of the EMD on a signal previously filtered by WMRA provides better results than its application on the original measured signal. The estimate of these statistical parameters was carried out by the signals belief by means of a slipping window whose size is about 1024 samples.

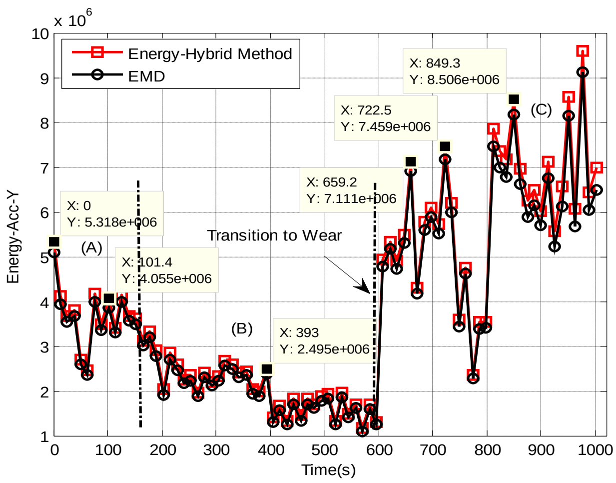

Figure 6: Energy evolution of the reconstructed signals with Hybrid method

We can note according from figure 6 that there is remarkable improvement in the scalar indicators reconstructed signals after application of the proposed approach are more significant and similar tendency. We also notice the transition of wear between the three phases is clearly detectable at an early date. Obviously, the scalar indicators of Hybrid method has the highest statistical significance in the last phase corresponding to the wear acceleration the indicator considerably increases and reaches a very important value of E = 9.585E+6 and Pmoy = 1.498E+6, with lifetime = 976.1 s, followed by the first phase corresponding to the Running-in phase with E = 4.174E+6 and Pmoy = 6.521E+5, with lifetime = 76.06 s, whereas wear stabilization phase was found to be less significant.

The results were very encouraging given that the correlations obtained were very satisfactory.

7 Conclusion

As the majority of vibration signals of the cutting process have a non-stationary nature, time-frequency methods were then used, namely Wavelet Multi-Resolution Analysis (WMRA) and Empirical Mode Decomposition (EMD). They are also used as an effective tool allowing the improvement of the sensitivity of scalar indicators. However, their reliability is immediately limited in the presence of high levels of background noise and other machine components. A hybrid method (WMRA/EMD) is finally proposed as an effective tool which gives best results than the application of WMRA or EMD alone.

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