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A Review on Automatic Fault Detection and Diagnosis in a Single Point Cutting Tool Using Wavelet Analysis

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ABSTRACT

Tool wears monitoring continuous to be a major area of concern in machining. In order to produce quality products at reasonable cost tool condition monitoring becomes an important study for all the researchers. Another drawback of most of these works is that constant cutting parameters are used for entire tool life. The Monitoring system can detect tool breakage and tool wear conditions using very simple triaxial sensors, surface finish of machined parts and dimensional accuracy dependent on tool condition. This paper reviews in eight categories in TCM: singularity analysis for tool state estimation, Artificial Neural Network, signal de-noising, time- frequency analysis, feature extraction, density estimation of tool wear classification, k-star algorithm, histogram feature of vibration signal. This paper provides a comprehensive survey of the current research on wavelet analysis to TCM and also some new novel techniques for future studies in this area.

Keywords: Wavelet Analysis, Tool condition monitoring.

I. INTRODUCTION

The main aim of tool condition monitoring is that, to apply appropriate sensors signal processing and pattern recognition techniques to choose and predict the cutting tool state, so as to reduce loss brought about by tool wear are tool breakage/failure by this can so as to reduces the loss. In order to achieving an effective tool condition monitoring (TCM) system can ensure productivity and improve work piece quality so hence, has a major affect on machining efficiency [1].In machining contact between cutting tool, work-piece and the chips imposes pressure on the tool and leads the shapes of the tool to change either gradually as tool wear are abruptly has tool breakage/fracture [2].

Tool condition is defined on the basis of geometrical changes in the tool, direct monitoring methods like vision and optical approaches, which measure geometric parameters of the cutting tool, have been established [3-5]. The main advantage of direct method is that capturing actual geometric changes arising from wear of tool. Hence, direct measurements are very difficult to implement due to continuous contact between tool and work-piece, and impossible because of the presence of the coolant fluid. The direct methods use these technologies: touching trigger probes, optical, radioactive, proximity sensors and electrical resistance measurement techniques [6].The indirect approaches are achieved by deducing or correlating suitable sensor signals to tool wear states. They are used in different techniques such as cutting forces, acoustic emission, temperature, vibration, spindle motor current and torque [7].

However, vibration measurement for machinery condition monitoring is easy, less costly and yields a great deal of information that can be used to monitor the relative motion between the tool tip and the work piece for precision of the cutting operation [8].Have reported that vibration analysis is widely accepted as a tool to monitor the operating conditions of a machine as it is nondestructive, reliable and permits continuous monitoring without intervening with the process [9].Li discusses the use of wavelet transforms to decompose acoustic emission signals and the root mean square(RMS) values of the decomposed signals are taken as tool wear monitoring features [10].Proposed to use wavelet transforms to analyze cutting force signals and wavelet transform coefficients are taken as recognition parameters of flank wear states.

2. Wavelet Analysis(Wavelet Transform)

Wavelet transform is one of the most useful tools for various signals processing application. Wavelet transform consists of coefficients that are the inner products of the signal and a family of wavelets. It analyses the low-frequency content of a signal with a wide duration function and conversely analysis high-frequency content with a short-duration function. It helps in decomposing a signal into different frequency components (scale), and it gives the information about the signal both in frequency and time domains as it can be used to analyze non-stationary signals. It can classify into continuous (CWT).Discrete (DWT) and Wavelet packet transforms (WPT).

Continuous Wavelet Transform (CWT):

A wavelet is a wave-like oscillation that instead of oscillating forever like harmonic wavesdrops rather quickly to zero. The continuous wavelet transform breaks up a continuous function f (t) into shifted and scaled versions of the mother wavelet ψ. It can be defined as the convolution of the input data sequence with a set of functions generated by the mother wavelet:

$$CW(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t).\psi(\frac{t-b}{a})dt \quad (1)$$

With the inverse transform being expressed as:

$$f(t) = \frac{1}{C\psi} \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} CW(a,b).\frac{1}{a}.\Psi\left(\frac{t-b}{a}\right)dadb \quad (2)$$

Where α represents scale (or pseudo-frequency) and b represents time shift of the mother wavelet ψ. ψ* is the complex conjugate of the mother wavelet ψ. The WT's superior time localization properties result from the finite support of the mother wavelet: as b increases ,the analysis wavelet scans the length of the input signal, and an increases or decreases in response to changes in the signal's local time and frequency content. Finite support implies that the effect of each term in the wavelet representation is purely localized. This sets the WT apart from the Fourier Transform, where the effects of adding higher frequency sine waves are spread throughout the frequency axis. CWT can be applied with higher resolution to extract information with higher redundancy, that is, a very narrow range of scales can be used to pull details from a particular frequency band.

3. Signal Analysis and Feature Extraction:

The objectives of TCM can be formally specified to be a search for the most probable state C_i
Given the extracted measurable signal feature y (t) at a time t. hence, as the pattern recognition problem, the aim of TCM is to find,

TCM:arg_i max p (C_i/y) (3)

Or in the physical form

TCM:arg_i max p (tool state /signal features)(4)

3.1 Signal Processing for Advanced Fault Diagnosis:

1) Wavelet transforms (Time-frequency analysis)
2) EMD (Empirical mode decomposition)
3) Hilbert Spectrum
4) AR-MED filter
5) Spectral Kurtosis (SK)
6) Cyclo-stationary analysis (Frequency-frequency analysis)

1. A Drawback of Fourier analysis:

- ✓ In Fourier analysis, sin/cos functions are used for sine functions basis function.
- ✓ Fourier analysis could not represent time-domain information. (Only frequency information)

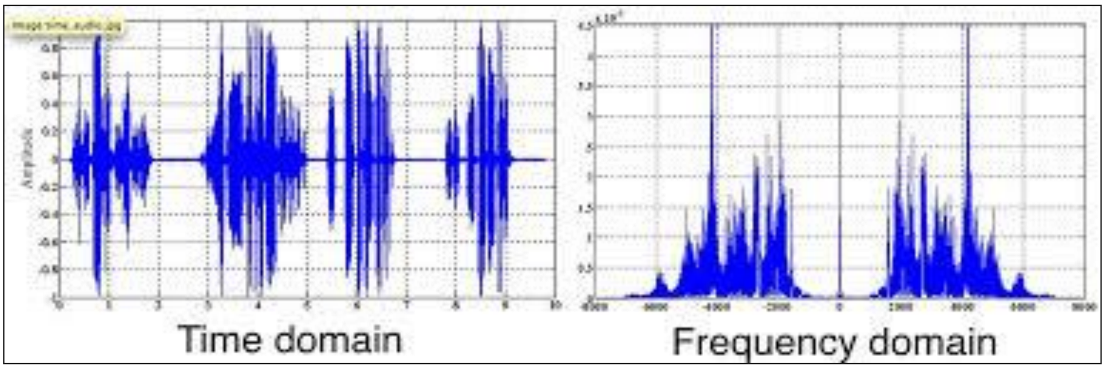

Fig.5. Time Domain & Frequency Domain

2) EMD (Empirical mode decomposition):

- ✓ Empirical: based on testing or experience
- ✓ Mode: a particular form or variety of something
- ✓ Decomposition (decompose): to separate into constituent parts orElements or into simpler compounds.

- ✓ Identify local maxima and minima in the signal
- ✓ Deduce an upper and a lower envelope by interpolation (cubic splines)
  - subtract the mean envelope from the signal
  - iterate until #{extrema} = #{zeroes} ±1
- ✓ subtract the so-obtained Intrinsic Mode Function (IMF) from the signal
- ✓ Iterate on the residual

3) Hilbert Spectrum:

The Hilbert transform is important in signal processing, where it derives the analytic representation of a signal u (t). This means that the real signal u (t) is extended into the complex plane such that it satisfies the Cauchy–Riemann equations. For example, the Hilbert transform leads to the harmonic conjugate of a given function in Fourier analysis, aka harmonic analysis. Equivalently, it is an example of a singular integral operator and of a Fourier multiplier.

HT [f (t)] = $\hat{f}$ (t) =f (t) *h (t),wereh (t) = $\frac{1}{\pi t}$ (5)

Relationship with the Fourier transforms (FT)

Fourier Transform of$\hat{f}$(t) $\hat{f}$ (t) =f (t) *h (t) $\Leftrightarrow \hat{F}$ (w) = F (w) H (w)

4) AR-MED filters:

- ✓ Combination of AR filter and MED filter
- ✓ AR filter: Autoregressive filter
- ✓ MED filter: Minimum Entropy De-convolution filter
- ✓ Widely used for fault diagnosis of rolling element bearings

5) Spectral kurtosis:

- ✓ Kurtosis* : Kurtosis (x) = $\frac{E\{(x-\mu)^4\}}{\sigma^4} - 3$ To make kurtosis of normal distribution 0
- ✓ Spectral kurtosis (SK) extends the concept of kurtosis to that of a function of frequency that indicates how the impulsiveness of a signal.

6) Cyclo-Stationary:“In search of hidden periodicities”

A cyclo-stationary process is a signal having statistical properties that vary cyclically with time. A cyclo-stationary process can be viewed as multiple interleaved stationary processes. The cyclo- stationary features is intentionally embedded in the physical properties of a communicational signal, which may be easily generated, manipulated, detected and analyzed using low complexity transceiver architectures. This feature is present in all transmitted signals, requires little signaling overhead may be detected using short signal observation times, and thus it can be used for primary user signal detection and recognition.

- ✓ Ensemble average: Mean of a quantity that is a function of the microstate of a system.

$$m_x(t) = E\{x(t)\} \triangleq \lim_{n-\infty} \frac{\sum xn(t)}{N} \quad (6)$$

- ✓ Stationary signals are random signals of zero cycle with 0 ensemble avg.
- ✓ Periodic signals are deterministic signals (don’t need an ensemble).

4. CONCLUSION:

Wavelet is a relatively new theory; it has enjoyed a tremendous attention and success over the last decade, and for a good reason.Almost all signals encountered in practice call for a time-frequency analysis, and wavelets provide a very simple and efficient way to perform such an analysis.Still, there’s a lot to discover in this new theory, due to the infinite variety of non-stationary signals encountered in real life.This review presents the use of wavelet transform for a given feature extraction.Mathematical basis of the wavelet transform has proved that signal analysis based on wavelet transform coefficients can be used very efficiently for the estimation of cutting tool features. Cutting tool feature extraction can be further improved by various methods but one of the most important problems is in the right definition of cutting tool features using both its frequency-domain and time-domain properties. From survey I came to know that, for signal analysis many techniques are available, selection of these are based on the experience or theoretical knowledge.

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