International Journal of Machine Tools & Manufacture 49 (2009) 537–553

Contents lists available at ScienceDirect

International Journal of Machine Tools & Manufacture

journal homepage: www.elsevier.com/locate/ijmactool

Wavelet analysis of sensor signals for tool condition monitoring: A review and some new results

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ARTICLE INFO

Article history:
Received 9 May 2008
Received in revised form
10 February 2009
Accepted 12 February 2009
Available online 27 February 2009

Keywords:
Wavelet
Tool condition monitoring

ABSTRACT

This paper reviews the state-of-the-art of wavelet analysis for tool condition monitoring (TCM). Wavelet analysis has been the most important non-stationary signal processing tool today, and popular in machining sensor signal analysis. Based on the nature of monitored signals, wavelet approaches are introduced and the superiorities of wavelet analysis to Fourier methods are discussed for TCM. According to the multiresolution, sparsity and localization properties of wavelet transform, literatures are reviewed in five categories in TCM: time–frequency analysis of machining signal, signal denoising, feature extraction, singularity analysis for tool state estimation, and density estimation for tool wear classification. This review provides a comprehensive survey of the current work on wavelet approaches to TCM and also proposes two new prospects for future studies in this area.

Contents

1. Overview of tool condition monitoring

1.1. Introduction

During machining, the contact between the cutting tool, workpiece, and the chips imposes pressure on the tool and causes the shape of the tool to change, either gradually as tool wear or abruptly as tool fracture or breakage [1]. In tool condition monitoring, the aim is to apply appropriate sensor signal processing and pattern recognition techniques to identify and predict the cutting tool state, so as to reduce loss brought about by tool wear or tool failure. An effective tool condition monitoring (TCM) system can improve productivity and ensure workpiece quality, and hence, has a major influence on machining efficiency [2]. Tool condition monitoring has been extensively studied by many researchers since the late 1980s. Many of the reported research works are reviewed in [3–5].

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doi:10.1016/j.ijmachtools.2009.02.003

Nomenclature

AE	acoustic emission
AR	autoregressive
ART	adaptive resonance theory
CQF	conjugate quadratic filters
CWD	Choi–Williams distribution
CWT	continuous wavelet transform
DFT	discrete Fourier transform
DWT	discrete wavelet transform
EMD	empirical mode decomposition
FDR	Fisher's discriminant ratio
FFT	fast Fourier transform
FWT	fast wavelet transform
GMM	Gaussian mixture models
HMM	hidden Markov models
ICA	independent component analysis
KLT	Karhunen–Loeve transform
LE	Lipschitz exponent
LDA	linear discriminant analysis
MLP	multilayer perceptron
MRA	multiresolution
NN	neural networks
PCA	principal component analysis
pdf	probability density function
PSD	power spectrum density
SNR	signal-to-noise ratio
SOM	self-organizing map
STFT	short-time Fourier transform
TCM	tool condition monitoring
WPD	wavelet packet decomposition
WT	wavelet transform
WTMM	wavelet transform modulus maxima
WVD	Wigner–Ville distribution

Symbols

$f(t)$	any mathematical signal $f(t)\in L_R^2$
$x(t)$	any sensory signal from machining
$y(t)$	extracted features
$\hat{f}(\omega)$	Fourier transform of $f(t)$
T_s	sampling interval
f_s	sampling frequency
C_i	class i
$\langle x(t),y(t)\rangle$	inner product of signal $x(t)$ and $y(t)$
u	position parameter of wavelet function
s	scale parameter of wavelet function
σ_t	the resolution of time
σ_ω	the resolution of frequency
$\psi(t)$	wavelet function
$\varphi(t)$	scaling function
$h(n)$	low-pass filter
$g(n)$	high-pass filter
$c_{j,k}$	scaling coefficient
$d_{j,k}$	wavelet coefficient
$W_{j,n,k}$	wavelet packet
$d_{j,k}^n$	wavelet packet coefficient
Q	quality factor
α	Lipschitz exponent
S_i	the covariance matrix of class i
S_W	within-class covariance matrix
S_B	between-class covariance matrix

Since tool condition is typically defined according to the geometrical changes in the tool, direct monitoring methods such as vision and optical approaches, which measure the geometric parameters of the cutting tool, have been developed [6–8]. The direct methods have advantages of capturing actual geometric changes arising from wear of tool. However, direct measurements are very difficult to implement because of the continuous contact between the tool and the workpiece, and almost impossible due to the presence of coolant fluids. The difficulties severely limit the application of direct approach. The indirect approaches are achieved by correlating or deducing suitable sensor signals to tool wear states. They have the advantages of less complicated setup and suitability for practical application. This paper focuses on indirect approaches. For indirect approaches, tool condition is not captured directly, but estimated from the measurable signal feature. This signal feature is extracted through signal processing steps (Fig. 1) for sensitive and robust representation of its corresponding state.

Indirect methods such as those based on sensing of the cutting forces [9–15], vibrations [16–20], acoustic emission (AE) [21–26], and motor/feed current [27–32] have been the most employed and reported for TCM. Detailed works on the design and implementation of these indirect approaches for TCM have been reported in [33–35].

1.2. TCM as a pattern recognition problem

The problem of TCM can be considered as a typical pattern recognition problem. 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 time t. This is a dynamic inference problem since the tool state is not estimated only with prior knowledge, but also adapt to the current features. This is somewhat of Bayesian inference [36].

Hence, as the pattern recognition problem, the aim of TCM is to find,

$$\text{TCM}: \quad \arg\max_i p(C_i|y) \tag{1}$$

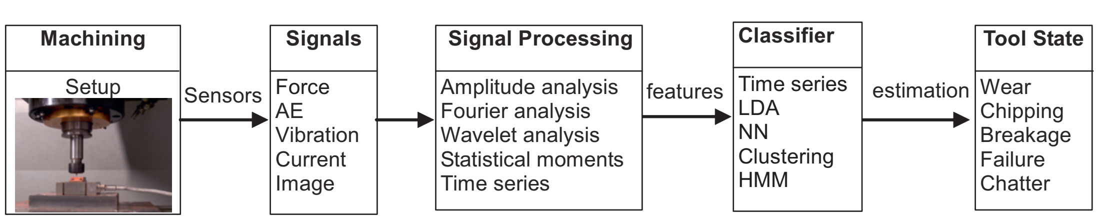

Fig. 1. The framework of TCM.