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An intelligent chatter detection method based on EEMD and feature selection with multi-channel vibration signals

Yun Chen[a], Huaizhong Li[b,*], Liang Hou[a], Jun Wang[c], Xiangjian Bu[a]

[a] Department of Mechanical and Electrical Engineering, Xiamen University, Xiamen, China
[b] Griffith School of Engineering, Gold Coast Campus, Griffith University, Australia
[c] School of Mechanical and Manufacturing Engineering, University of New South Wales, Sydney, Australia

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ABSTRACT

Chatter detection in metal machining is important to ensure good surface quality and avoid damage to the machine tool and workpiece. This paper presents an intelligent chatter detection method in a multi-channel monitoring system comprising vibration signals in three orthogonal directions. The method comprises three main steps: signal processing, feature extraction and selection, and classification. The ensemble empirical mode decomposition (EEMD) is used to decompose the raw signals into a set of intrinsic mode functions (IMFs) that represent different frequency bands. Features extracted from IMFs are ranked using the Fisher discriminant ratio (FDR) to identify the informative IMFs, and those features with higher FDRs are selected and presented to a support vector machine for classification. Single-channel strategies and multi-channel strategies are compared in low immersion milling of titanium alloy Ti6Al4V. The results demonstrate that the two-channel (*Ay*, *Az*) strategies based on signal processing and feature ranking/selection give the best performance in classification of the stable and unstable tests.

1. Introduction

Machining operations are enhanced due to the development of new concepts, devices, materials, tools and structures. However, machining stability is still a limitation which may cause poor surface quality, reduced tool life, and even breakage of cutting tools in metal removal processes [1]. One of the main problems with machining stability is chatter, which is a self-induced vibration between the cutting tool and workpiece with complex, nonlinear and nonstationary characteristics. In order to avoid chatter, extensive studies have been devoted to obtain the stability chart in the two-dimensional space of the spindle speed and depth of cut [2]. However, those studies require a complete analysis of the machining system dynamics and in-depth knowledge of the machining process and material properties, which is difficult for industrial users. On the other hand, intelligent monitoring is preferred in industrial applications, given the recent advances in sensors and signal processing techniques.

For an accurate diagnose of the machining process, monitoring systems rely on usage of sensors to detect tool or workpiece malfunctions. Dynamometers [3], accelerometers [4], microphones [5] and AE sensors [6] are commonly-used sensors to monitor the machining operations. Delio et al. [7] compared the three types of sensors for chatter detection and control. The results indicated that the force signals failed to adequately reflect chatter in low-immersion and low-feed machining operations due to the short contact time, whereas microphones were more suitable to chatter detection than other remotely placed displacement sensors. Nevertheless, microphones are limited by directional considerations, low frequency response and environmental sensitivity. The suppression of environmental noise is mandatory for chatter detection using microphones [8]. Kuljanic et al. [9] investigated multi-sensor approaches for chatter detection, and the results showed that a multi-sensor system composed of the axial force sensor and accelerometers gave the best results than any single-sensor or multi-sensor system in their investigated milling system.

Signal processing techniques extract from the signals the features related to chatter. Those features can be used as either chatter indicators or inputs to an intelligent system for chatter detection. Schmitz et al. [10] evaluated the statistical variance in the once-per-revolution sampled AE signal during milling as a chatter indicator. Vela-Martinez et al. [11] used a fractal rescaled range analysis method to evaluate signal fractality that is related to changes in machining stability. Patwari et al. [12] used the fast Fourier transform (FFT) to analyse chatter that is generated by chip serration in titanium machining. Alternatively, the time-frequency analysis techniques are used for feature extraction.

* Corresponding author at: School of Engineering and Built Environment, Gold Coast Campus, Griffith University, QLD 4222, Australia.
E-mail address: h.li@griffith.edu.au (H. Li).

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The wavelet packet [13], Wigner time-frequency [14] and Hilbert-Huang transform [4] have been used to different machining systems for chatter detection. The time-frequency methods predominate over the time or frequency analysis methods, as they can reflect the nonstationary properties of signals over time.

Chatter is related to the dynamic behavior of the machine-tool-workpiece system. There is a frequency-dependent energy rise around system natural frequencies when chatter occurs. The frequency bands that cover the natural frequencies are usually extracted from the raw signals, therefore highlighting the incipient characteristics and improving the sensitivity of the detection method. Lamraoui et al. [15] designed a multiband resonance filtering to process the signals before feature extraction. Yao et al. [16] applied a wavelet packet transform to decompose the raw signals and identify the most sensitive frequency bands related to chatter. From those components, statistical features, such as mean, variance, skew and kurtosis can be extracted to describe the raw signals. However, not all features can adequately reflect the changes in the machining states. Hence, a feature selection criterion or reduction method is needed [17]. Dong et al. [18] applied neural networks to select relevant features, and Lamraoui et al. [15] ranked features according to relative entropy measure. In-depth discussions about feature selection techniques can be found in the review papers [17,19].

The role of pattern recognition methods employed in the implementation of intelligent monitoring systems is a fundamental one. A number of techniques have been used to detect chatter based on sensor signal features. Siddhpura and Paurobally [20] and Teti et al. [17] in their review papers stated that neural network and fuzzy logic techniques are widely used in tool condition monitoring. Other methods, e.g. Gaussian mixed model [21] and support vector machine [16], have also been employed to recognize the machining states. In some cases, a single sensory source for measuring a particular variable may not be able to meet all the required performance specifications. A solution to this problem is data fusion that combines multiple data sources so that the results may be better than those when these sources are used individually [17]. In order to develop an intelligent multi-sensor chatter detection system, Kuljanic et al. [8] used four decision-level fusion strategies including linear combination of sensor chatter indicators, neural network, fuzzy logic and statistical inference. The results indicated that the statistical inference strategy achieved the highest levels of accuracy among all the fusion strategies. Based on the combination of three types of sensors, Segreto et al. [6] obtained a high success rate in the assessment of tool wear in nickel alloy turning using a back-propagation neural network.

This paper presents a study on chatter detection in a multi-channel monitoring system. The ensemble empirical mode decomposition (EEMD), an improvement of the empirical mode decomposition (EMD), is employed to decompose the raw signals into a set of intrinsic mode functions (IMFs) with varied frequency bands. Features extracted from each IMF are ranked based on the Fisher discriminant ratio (FDR), and top ranked features are selected to a linear support vector machine (SVM) for classification. Single channel strategies and multi-channel strategies are compared by assessing the vibration signals from three sensory channels in low immersion end milling titanium alloy Ti6Al4V under various cutting conditions. The methodology, experimental setup and analysis results are presented in the following sections.

2. Methodology

Chatter is a nonlinear and nonstationary dynamic instability, whose energy at specific frequency ranges varies according to the dynamic characteristic of the machining system [8,22]. It is not practical to determine such dynamic characteristic in industrial conditions. In order to obtain a monitoring system independent from the system dynamics, signal processing techniques and intelligent classification methods are conceived. The work aims to develop an intelligent chatter detection method based on EEMD and feature selection in a multi-channel monitoring system. EEMD that is a self-adaptive analysis for nonlinear and nonstationary signals decomposes signals into IMFs, which limits chatter frequencies in narrow frequency bands and highlights chatter characteristics. Moreover, when analyzing intermittent and noisy signals produced in interrupted low immersion milling, EEMD generates more effective IMFs than EMD without mode mixing. In order to improve the classification accuracy and save computation time, features with high separability capabilities are selected from the informative IMFs for classification. The fusion techniques of multi-channel signals are investigated and utilized to further improve the classification accuracy. The procedures for the proposed approach are discussed in detail in the following subsections.

2.1. Ensemble empirical mode decomposition

The EMD adaptively decomposes a nonstationary signal to a set of IMFs that represents simple oscillatory modes as a counterpart to the harmonic functions. Using EMD, an arbitrary signal $s(t_n)$ can be decomposed into I oscillatory modes and the residue r_i

$$s(t_n) = \sum_{i=1}^{I} c_i(t_n) + r_i \tag{1}$$

where t_n is the nth discrete time and c_i is the ith IMF. Due to the adaptive property of EMD, the oscillatory mode with the highest frequency band of the signal $s(t_n)$ is decomposed into the first IMF c_1, and subsequent IMFs with progressively lower frequency bands.

In order to improve EMD, Huang and Wu [23] used white noise to homogenize the whole time-frequency space and enhance the projection of different components of the signal into proper IMFs. The procedures of EEMD are as follows:

i. Add a white noise series w_j ($j = 1, 2,\ldots, J$) with a zero mean and constant amplitude to $s(t_n)$ in the jth trial.

$$S_j(t_n) = s(t_n) + w_j \tag{2}$$

i. Decompose $s_j(t_n)$ using EMD to generate IMFs $c_{ij}(t_n)$.
ii. Given an ensemble number of J, the final ith IMF is the ensemble mean of corresponding IMFs of all the trials

$$c_i(t_n) = \frac{1}{J}\sum_{j=1}^{J} c_{ij}(t_n) \tag{3}$$

The ensemble number J should be large enough to decrease or completely cancel the added white noise by the ensemble means. An ensemble number of a few hundred will usually lead to an accurate result [23]. Yeh et al. [24] suggested that the amplitude of white noise should not be more than 20% of the standard deviation of the signal.

2.2. Feature extraction and selection

In order to describe the signals, the statistical features that are correlated with the machining states are extracted from each IMF. Different methods have been applied for feature extraction in time, frequency, or in time-frequency domains. In this work, seven features are investigated for chatter detection: energy ratio, peak-to-peak value (P2P), standard deviation of P2P per revolution, root mean square (RMS), crest factor, skewness and kurtosis. Table 1 lists the features for each IMF.

It is noted that the sensitivities of different features to chatter vary. Those features that are the most significant and reliable can help design a classifier with good performance. For this reason, the feature selection procedure is necessary. The FDR is used to rank features, and helps to select the top ranked features for chatter detection. The FDR of an individual feature in the two-class problem is defined as