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Chatter detection in milling process based on the energy entropy of VMD and WPD

Zhao Zhang, Hongguang Li*, Guang Meng, Xiaotong Tu, Changming Cheng

State Key Laboratory of Mechanical System and Vibration, School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

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ABSTRACT

This paper presents a novel approach to detect the milling chatter based on energy entropy. By using variational mode decomposition and wavelet packet decomposition, the cutting force signal is decomposed into two group of sub-signals respectively, and each component has limited bandwidth in spectral domain. Since milling chatter is characterized by the change of frequency and energy distribution. Therefore the energy features extracted from the two group of sub-signals are considered and the energy entropies are obtained, which can be utilized to demonstrate the condition of the milling system synthetically. Several milling tests are conducted and the results show that the proposed method can effectively detect the chatter at an early stage.

1. Introduction

It is well recognized that milling chatter is one of the biggest obstacles in achieving high performance machining operations due to its detrimental nature. Some profound reviews about the chatter problems, e.g. the chatter prediction, chatter detection and chatter control strategies, have been provided by Ehmann and Kapoor [1], Altintas and Weck [2], Quintana and Ciurana [3], Siddhpura and Paurobally [4]. It is noted that the chatter prediction is difficult for industrial users to carry out, hence chatter detection becomes essential for maintaining efficient machining process and the realization of control strategies for chatter suppression.

In order to monitor the cutting status, various sensors and signals have been used, for example, displacement signal [5,6], acceleration signal [7–11], cutting force [12–15], acoustic emission [16-19], motor current [20,21]. No matter which signal is chosen, the method of signal processing is much more important. Therefore, appropriate feature extraction should be defined for detection in relation to the signal processing, including the time series modeling [10], the spectral analysis [12,18,22,23], and the time–frequency analysis [9,14,24]. There are other available methods as well. For instance, Cao et al. [11] adopted the ensemble empirical mode decomposition to analyze vibration signal, then the C0 complexity and power spectral entropy are extracted as chatter indicators; Vela-Martíneza et al. [25] presented an approach to monitor the evolution of cutter tool dynamics with detrended fluctuation analysis. Several smart algorithms were also introduced so far, such as artificial neural network [26,27], fuzzy logic [28].

Milling chatter is a nonlinear and non-stationary phenomenon. Since the Fourier transform methods conceals the time-domain information, hence it is blind to state transition in non-stationary signals and ineffective for on-line detection of chatter onset. Time–frequency analysis offers an alternative method to identify fault feature for non-stationary process, e.g. variational mode decomposition (VMD) and wavelet packet decomposition (WPD). VMD can decompose a multi-component signal into a discrete number of sub-signals with the specific sparsity properties of its bandwidth in the spectral domain [29]. WPD is an expansion of classical wavelet decomposition, which splits the signal both the low-pass band and high-pass band at all stages. The VMD and WPD have been widely used for non-stationary signals, such as the rolling bearing fault diagnosis [30,31], physiological signal denoising [32] and cutter tool monitoring [33].

It is well known that regenerative chatter is caused by the interaction of the workpiece and cutting tool. Chatter is characterized by the change of frequency and energy distribution [34]. In the stable milling process, the energy of the tool is dominated by its rotation frequency and harmonics. When chatter occurs, the energy is absorbed to the chatter frequency gradually. Hence, a method for the detection of milling chatter based on the change of energy distribution is proposed in this paper. First the cutting

* Corresponding author.
E-mail address: hgli@sjtu.edu.cn (H. Li).

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Table 1
Cutting conditions.

Group	Test	Milling type	Radial depth of cut (mm)	Axial depth of cut (mm)	Cutting speed (mm/min)	Spindle speed (r/min)
I	1	Up	4	2.9	108	3600
II	2	Down	slot	0.4	198	6600
	3	Down	slot	0.6	198	6600
	4	Down	slot	0.7	198	6600
III	5	Down	2	0.4	108	3600
	6	Down	2	2.0	108	3600
	7	Down	2	4.0	108	3600
IV	8	Down	slot	0.3	144	4800
	9	Down	slot	0.4	144	4800
	10	Down	slot	0.6	144	4800
	11	Down	slot	0.7	144	4800
V	12	Down	5	0.5	216	7200
	13	Down	5	0.6	216	7200
	14	Down	5	4.0	216	7200
VI	15	Down	3	0.7	234	7800
	16	Down	3	0.8	234	7800
	17	Down	3	3.0	234	7800
	18	Down	3	3.2	234	7800

force signal is decomposed into two group of sub-signals by VMD and WPD respectively. Then the energy features are extracted from the two group of sub-signals and the energy entropies are obtained to demonstrate the condition of the milling system. The effectiveness of the proposed method is validated by a series of milling tests. The results show that the proposed method provides a new way to extract the feature of weak chatter signals under any cutting condition.

2. Methodology

2.1. Variational mode decomposition

VMD is an adaptive and non-recursive signal decomposition method proposed by K. Dragomiretskiy and D. Zosso [29] in 2014. In the VMD framework, the signal is decomposed into k discrete number of sub-signals, and each component is considered compact around a corresponding center frequency. The bandwidth of a component can be evaluated with constrained variational optimization problem, and the formulated constrained variational problem can be expressed as follows:

$$\min_{\{u_k\}\{\omega_k\}}\left\{\sum_k \|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)\times u_k(t)\right]e^{-j\omega_k t}\|_2^2\right\} \quad \text{s.t.} \sum_k u_k = f \tag{1}$$

where u_k is the kth component of the signal, and the ω_k denotes center frequency of the kth component of the signal, f is the origin signal, δ is the Dirac distribution, t is time script.

By introducing a quadratic penalty and Lagrangian multipliers, the above constrained optimization problem can be expressed as [29]:

$$L(\{u_k\},\{\omega_k\},\lambda) := \alpha\sum_k\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 + \left\|f(t)-\sum_k u_k(t)\right\|_2^2 + \left\langle \lambda(t), f(t)-\sum_k u_k(t)\right\rangle \tag{2}$$

where α denotes the balancing parameter of the data-fidelity constraint.

Then Eq. (2) can be solved by the alternate direction method of multipliers (ADMM), the estimated components in frequency domain are as follows:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i\neq k}\hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega-\omega_k)^2} \tag{3}$$

where $\hat{f}(\omega)$, $\hat{u}_i(\omega)$, $\hat{\lambda}(\omega)$ and $\hat{u}_k^{n+1}(\omega)$ the Fourier transforms of $y(t)$, $y_i(t)$, $\lambda(t)$ and $y_k^{n+1}(t)$.

It is noted that Eq. (3) contains the Wiener filter structure. The component in time domain can be obtained from the real part of inverse Fourier transform of the filtered signal.

2.2. Wavelet packet decomposition

WPD is a wavelet transform where the discrete time signal is passed through more filters than the discrete wavelet transform (DWT). It is an extension of the DWT. Instead of dividing only the approximations of the signal, the details are also divided. Therefore, WPD can further decompose the detail information of the signal in the high frequency region.

For j levels of decomposition, the WPD produces 2^j different sets of coefficients $x_m^j(t)$ for a data vector with n data points, where, $m=1, 2, \ldots, 2^j$, are the number of sets, and the length of $x_m^j(t)$ is $n/2^j$. According to the wavelet packet coefficients of different sets, the signal in different frequency region of $[f_s(m-1)/2^j$ $f_s m/2^j]$ can be reconstructed as $p_m^j(t)$, where f_s is the sampling frequency. The wavelet packet coefficients could be an indication of certain features of the analyzed signal.

2.3. Energy entropy

In the stable milling process, the energy of the milling system is mostly dominated by its rotation frequency and harmonic frequencies. When chatter occurs, the energy is absorbed to the chatter frequency gradually. Hence the frequency and energy distribution are closely related to the milling conditions, which can be illustrated by energy entropy.