Monitoring of Tool Wear States in Turning Based on Wavelet Analysis*

Weiguo GONG**, Toshiyuki OBIKAWA***
and Takahiro SHIRAKASHI***

In this paper, a novel signal processing tool, the wavelet transform, was applied to monitor the flank wear states in turning. The wavelet transforms were implemented by FWT (fast wavelet transform) based on a QMF (quadrature mirror filter). The expansion coefficients $d(j, k)$ with time-frequency feature obtained by FWT were used as recognition parameters of the flank wear states. The dynamic characteristics of the cutting force signals were analyzed separately using the wavelet transform and the Fourier transform. The abilities of these two transforms for analyzing and recognizing the flank wear states were compared. The experimental and analytical results show that when monitoring the flank wear states during turning, the wavelet analysis is more sensitive, more reliable and faster than the Fourier analysis.

Key Words: Turning, Tool Wear, Cutting Force, Monitoring, Wavelet Analysis, Quadrature Mirror Filter.

1. Introduction

A fast and reliable signal processing technique is an important necessity when developing an automatic monitoring system for machining processes.

In recent years, wavelet transforms have been effectively used as a new analytical tool by mathematicians, signal analysts and engineers. This is because the transform's excellent properties have been successfully and widely applied to the numerical solutions of partial differential equations, multidimensional image representation and processing, speech coding, pitch detection, audio compression, edge detection, transient detection, signal interpolation, seismic signal analysis, radar image, and array processing⁽¹⁾⁻⁽⁶⁾.

In manufacturing engineering, wavelet trans-

forms are being applied for the detection of cutting tool failure, especially tool breakage, and the analysis of machine tool vibration. Tansel^{(7),(8)} obtained a set of compressed patterns with the tool failure features using the wavelet transform of the Daubechies-type wavelet system in micro-drilling and end milling. Kawai⁽⁹⁾ used a Gaussian wavelet to analyze the time-frequency spectrum of cutting sounds in normal and abnormal states of a milling cutter. Kasashima⁽¹⁰⁾ used the Daubechies-type wavelet system, similar to Tansel's, to detect the chipping of the cutter in the face milling process. The results of their studies show that the prospects for machining process monitoring are very good.

In signal analysis, the Fourier transform has been used as the keystone of modern signal processing. It, however, has a problem in that it transforms the signal from a time domain to a frequency domain assuming that the signals are stationary or infinite in nature. Namely, it has a difficulty in describing transient components, such as shortly decaying frequency components, and it does not convey any information pertaining to translation of the signal from the time domain to the frequency domain. Attempts to solve

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** Department of Mechano-Aerospace Engineering, Tokyo Institute of Technology. Presently, System & Control Division, Nisshin Denshi Seigyo Corporation, Sasazuka, Shibuya-ku, Tokyo 151, Japan

*** Department of Mechano-Aerospace Engineering, Tokyo Institute of Technology, O-okayama, Meguro-ku, Tokyo 152, Japan

these problems, e.g., the development of the short-time Fourier transform (STFT), have met with marginal success.

The wavelet transforms, however, need not have infinite duration because their basic functions are unlike the harmonic functions of the Fourier transform. They can be nonzero for only a small range of the wavelet function. If their energy is localized to a finite space in time, that is, the wavelet system has a "compact support", the wavelet transform is allowed to translate a time-domain function into a representation that is localized not only in frequency but also in time. These properties have not only overcome the problems of the Fourier transform but have also brought forth new developments in the fields of signal analysis, image processing and data compression.

This paper used the real-valued wavelet transform of the cutting force to monitor the flank wear states in the turning process. The wavelet transforms were implemented through finite impulse response filters called a "Quadrature Mirror Filter" (QMF) pair designed by Daubechies⁽⁴⁾. The expansion coefficients $d(j, k)$ with time-scale feature and multiresolution nature located at the level j , which is determined by the dynamic characteristics of the tool vibratory system, were used as recognition parameters to monitor the flank wear states. The experimental and analytical results have shown that the monitoring method based on wavelet analysis can extract process information with characterized parameters from the raw cutting force signals and detect the development of flank wear more efficiently, more reliably and faster than that by Fourier analysis.

2. Wavelets and Fast Wavelet Transform

The continuous wavelet transform can be represented by the following equation⁽¹⁾:

$$CWT(a, b) = \frac{1}{\sqrt{|a|}} \int f(t) h^* \left(\frac{t-b}{a} \right) dt, \quad (1)$$

where a and b are the dilation and translation parameters, respectively. The parameter a is related to the frequency and the symbol $*$ denotes complex conjugation. From this equation it can be seen that the wavelet transform decomposes a signal $f(t)$ into a weighted set of scaled wavelet functions $h(t)$.

In practice, the wavelet calculations can be implemented in digital computers by the scaling function $\phi(t)$ and the basic function $\psi(t)$:

$$\phi(t) = \sum_{k \in Z} a_k \phi(2t - k) \quad (2.a)$$

$$\psi(t) = \sum_{k \in Z} (-1)^k a_{k+1} \phi(2t + k), \quad (2.b)$$

where Z is the set of integers and a_k is the wavelet coefficient. Both functions are two-scale difference equations. They are the prototypes of a class of

orthonormal basis functions (3) and (4):

$$\phi_{j,k}(t) = 2^{j/2} \phi(2^j t - k); \quad j, k \in Z \quad (3)$$

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k); \quad j, k \in Z, \quad (4)$$

where the parameters j similar to a in Eq.(1) and k similar to b in Eq.(1), control the dilation of the function and the translation of the function in time, respectively. The set of basis functions formed by $\phi(t)$ and $\psi(t)$ is a system of scaled and translated wavelets.

For any set of wavelet coefficients a_k , the following conditions must be satisfied:

$$\begin{aligned} \sum_{k \in Z} a_{2k} &= 1, \quad \sum_{k \in Z} a_{2k+1} = 1, \\ \sum_{k \in Z} a_k^2 &= 2, \quad \sum_{k \in Z} a_k a_{k+2m} = 0 \quad \text{for } m \neq 0. \end{aligned} \quad (5)$$

Among the several wavelet systems reported, the following formula which generates the real-valued wavelet system with six coefficients a_k was adopted in this paper⁽⁴⁾:

$$\begin{aligned} a_{-2} &= [(1 + \cos \alpha + \sin \alpha)(1 - \cos \beta - \sin \beta) \\ &\quad + 2 \sin \beta \cos \alpha] / 4 \\ a_{-1} &= [(1 - \cos \alpha + \sin \alpha)(1 + \cos \beta - \sin \beta) \\ &\quad - 2 \sin \beta \cos \alpha] / 4 \\ a_0 &= [1 + \cos(\alpha - \beta) + \sin(\alpha - \beta)] / 2 \\ a_1 &= [1 + \cos(\alpha - \beta) - \sin(\alpha - \beta)] / 2 \\ a_2 &= 1 - a_{-2} - a_0, \quad a_3 = 1 - a_{-1} - a_1, \end{aligned} \quad (6)$$

where $-\pi \leq \alpha, \beta < \pi$.

From Eq.(6) it can be seen that because the values of parameters α and β can be taken from $-\pi$ to $+\pi$, the wavelet coefficient generation system provides more flexible selection for signal processing analysts.

After a wavelet system is determined, if it has a compact support and the upper limit of the degree of dilation is n , a function $f(t)$ with the number of data points $N=2^n$ can be represented in terms of the functions $\phi(t)$ and $\psi(t)$ ⁽⁴⁾:

$$f(t) = \sum_{l \in Z} c(l) \phi_l(t) + \sum_{j=0}^{n-1} \sum_{k \in Z} d(j, k) \psi_{j,k}(t), \quad (7)$$

where

$$c(l) = \langle \phi_l | f \rangle = \int f(t) \phi_l(t) dt$$

$$d(j, k) = \langle \psi_{j,k} | f \rangle = \int f(t) \psi_{j,k}(t) dt,$$

where $c(l)$ and $d(j, k)$ are the expansion coefficients and can be calculated as the inner product of $f(t)$ and $\phi(t)$ or $\psi(t)$, respectively.

The expansion coefficients $c(l)$ and $d(j, k)$ in Eq.(7) represent, respectively, the approximation of the original signal $f(t)$ and the details of the original signal at different levels of resolution. These coefficients completely and uniquely describe the original signal and can be used in a similar way to the Fourier transform. Thus, the wavelet transform is a process used to determine the values of $c(l)$ and $d(j, k)$ for a given $f(t)$ and wavelet system.

To implement the fast wavelet transform

(FWT), the finite impulse response (FIR), called a QMF pair, proposed by Daubechies, can be used⁽⁶⁾. A QMF pair calculates the inner product between the coefficients and the discrete sample of the original signal $f(t)$ in the tapped delay line of the filter and separates the frequency responses of the input signal into its high-frequency and low-frequency components. This operation can be repeated recursively by means of a tree structure algorithm. Implementing this filter tree structure results in a bank of contiguous bandpass filters spread logarithmically over the frequency. The low-pass filter coefficients are associated with a_k of the scaling function $\phi(t)$ and the output of each low-pass filter is $c(l)$. The high-pass filter coefficients are associated with a_k of the basic function $\psi(t)$ and the output of the j times resolution is $d(j, k)$. The low-pass filter output $c(l)$ of the level j is used to generate $c(l+1)$ and $d(j+1, k)$ at the next level $j+1$ of the tree.

In this paper, the FWT algorithm, as mentioned above, was adopted and the multiresolution nature of the basic functions was used to extract the time-frequency information of the feed force with the development of the flank wear.

3. Experimental Setup and Analytical Results

Figure 1 shows the experimental setup of the flank wear monitoring system. The cutting force signals in the feed direction were detected by strain gauges attached to the shank of the cutting tool, then amplified through strain amplifiers, sampled and collected by a FFT analyzer, and processed using an off-line engineering workstation.

Before the experiments, the flank face of the tool tips used were ground to prepare an artificial flank wear land of 0.0 mm, 0.1 mm, 0.15 mm, 0.2 mm, 0.25 mm and 0.3 mm. The experiments using the same value of flank wear were repeated 10 times under the same cutting conditions to examine the experimental and analytical reproducibility. The experimental conditions are listed in Table 1, where it can be seen that the total number of cutting experiments is 540.

Fig. 1 Experimental setup

In the following wavelet analyses of the feed force signals, the multiresolution nature of the basic function is used to extract the time-frequency information with the development of the flank wear. The extracted information, the expansion coefficients $d(j, k)$, is used as a monitoring parameter of the flank wear.

In order to determine the frequency band for the wavelet analysis of the cutting force, the frequency response of the tool-free vibration was tested by an impulse excitation in the feed direction. Figure 2 shows the power spectrum of the tool-free vibration. Two main peak frequencies were identified. The first, 3 700 Hz, is related to the natural frequency of the tool in the feed direction, and the second, 4 000 Hz, is the natural frequency of the torsional vibration of the tool.

Figure 3 shows the typical waveforms of feed force signals in the time domain for different flank wears under the following cutting conditions: cutting speed, 120 m/min, feed rate, 0.1 mm/rev and depth of cut, 1 mm. Figure 3 shows that, with development of the flank wear, the static and dynamic components of the feed forces increase.

Figure 4 shows the power spectra of the feed force signals analyzed from the waveforms in Fig. 3. From Fig. 4, it can be seen that with an increase in tool flank wear, the peak frequency shifted toward 4 000 Hz, related to the torsional vibratory frequency

Table 1

Material	S45C, hardened and tempered
Cutting speed	120m/min
Feed rate	0.075, 0.1 and 0.125mm/rev
Depth of cut	1.0, 1.5 and 2.0mm
Tool flank wear	0.0, 0.1, 0.15, 0.2, 0.25 and 0.3mm
Lubrication	None
Tool	P20, -6°, 6°, -6°, 6°, 75°, 15°, 0.4mm

Fig. 2 Power spectrum of the free-vibration tool system

Fig. 3 Raw waveforms of feed force signal for progressive tool wear
Cutting conditions: cutting speed, 120 m/min, feed rate, 0.1 mm/rev and depth of cut, 1.0 mm

Fig. 4 Power spectrum of feed force signal for progressive tool wear
Cutting conditions: same as Fig. 3

of the tool. Because the main frequencies of the feed force signals with the development of tool wear were located from 3 700 Hz to 4 000 Hz, the frequency band to be analyzed was set from 3 200 Hz to 6 400 Hz to investigate the dynamic characteristics of the feed force over a wider frequency band around the main frequencies for the progressive tool wear. The sampling frequency of the FFT analyzer was 102.4 KHz and the data length for each sample process was 1 024 (taking 10 ms). In this frequency band, the parameter j was calculated to be 5 by the following formula:

$$j = \log_2(f_{\text{sampling}}/f_{\text{band-low}}),$$

where f_{sampling} is the sampling frequency and $f_{\text{band-low}}$ is the low-limit frequency of the analyzed frequency

Fig. 5 Variation of the expansion coefficients for progressive tool wear
Cutting conditions: same as Fig. 3

Fig. 6 Variation of the expansion coefficients $d(5, k)$ for progressive tool wear under different depth of cut
Cutting conditions: same as Fig. 3 except depth of cut

band. Thus, at resolution level $j=5$, 32 data points of the expansion coefficients $d(5, k)$ can be obtained by the fast wavelet transform conducted recursively five times.

Figure 5 shows the variant features of the expansion coefficients $d(5, k)$ of data sets of the feed force signals obtained from Fig. 3 for the progressive flank wear. In this paper, α and β in Eq. (6) were taken as $\pi/4$ and $\pi/10$, respectively. It can be seen that the values of the expansion coefficients $d(5, k)$, located from 3 200 Hz to 6 400 Hz, increase with the development of flank wear.

Figures 6(a) and 6(b) show the relationship between the variant features of the expansion coefficients $d(5, k)$ and the flank wear width for

different depth of cut, i.e., 1.5 mm and 2.0 mm. Figure 6 shows clearly the effect of the contact area between the machined surface of the workpiece and the tool flank wear on the expansion coefficients, $d(5, k)$. The expansion coefficients $d(5, k)$ are very sensitive to the depth of cut.

In order to describe more distinctly the correlation between the variations of the expansion coefficients $d(5, k)$ and the flank wear for different depth of cut, averaging of the expansion coefficients $d(5, k)$ was conducted. The average of the absolute values of 32 data points for the sets of expansion coefficients $d(5, k)$ gives a value $\bar{w}$:

$$\bar{w} = \left(\sum_{k=0}^{31} |d(5, k)| \right) / 32$$

Figure 7 shows the average features $\bar{w}$ of the expansion coefficients $d(5, k)$ for the progressive tool wear under different depth of cut. From Fig. 7 it can be seen that the expansion coefficients $d(5, k)$ located from 3 200 Hz to 6 400 Hz can distinctly express the changes of the flank wear states under different depth of cut.

Figure 8 shows the relationship between the variations of the expansion coefficients $d(5, k)$ and feed rates under the following experimental conditions: cutting speed, 120 m/min; depth of cut, 1 mm; feed rates, 0.075 mm/rev, 0.1 mm/rev and 0.125 mm/rev; and flank wear from 0.0 mm to 0.3 mm. In Fig. 8, it is very clear that the expansion coefficients $d(5, k)$ are affected by the feed rate; that is, they increase with the feed rate, especially for flank wear over 0.1 mm.

Figures 9 and 10 show the relationship between the average features $\bar{w}$ of the expansion coefficients $d(5, k)$ and feed rates under two depth of cut and four flank wear values separately. From these two figures

Fig. 7 Variation of the average expansion coefficients $\bar{w}$ for changes of depth of cut under different flank wear states
Cutting conditions: cutting speed, 120 m/min and feed rate, 0.1 mm/rev

Fig. 8 Variation of the expansion coefficients $d(5, k)$ with changes of feed rate under different flank wear states
Cutting conditions: cutting speed, 120 m/min and depth of cut, 1.0 mm

Fig. 9 Variation of the average expansion coefficients $\bar{w}$ with change of feed rate under different flank wear states
Cutting condition: same as Fig. 8

Fig. 10 Variation of the average expansion coefficients $\bar{w}$ with changes of feed rate under different flank wear states
Cutting conditions: cutting speed, 120 m/min and depth of cut, 1.5 mm

it can be clearly seen that the tool wear states under different feed rates and depth of cut can be well represented by the expansion coefficients $d(5, k)$ located between 3 200 Hz and 6 400 Hz.

Figure 11 represents the conclusive relationship between the average expansion coefficients $\bar{w}$ and the wear land areas for all the experimental conditions listed in Table 1. Their linear relations are excellent for a given feed rate and independent of the depth of cut.

When turning on a CNC lathe, tool engineers select the function of constant cutting speed to better manage the machined surface and tool life. Thus, the cutting speed and the feed rate are usually constant for a certain operation of roughing or finishing. On the other hand, the depth of cut often changes during the operation. In Fig. 11, the average expansion coefficient $\bar{w}$ is linear to the area of flank wear for constant cutting speed, constant feed rate and variable depth of cut. For this reason, the monitoring of the flank wear by means of wavelet analysis seems to be

Fig. 11 Variation of the average expansion coefficients $\bar{w}$ with different wear land areas
Cutting conditions: cutting speed, 120 m/min and depth of cut, 1.0 mm, 1.5 mm and 2.0 mm

Fig. 12 Variation of the spectral peak value with different wear land areas
Cutting conditions: same as Fig. 11

suitable and widely applicable to CNC turning.

To compare the applicability of the wavelet analysis to the flank wear monitoring with that of the Fourier analysis, the relationships between the peak values of the power spectrum of the feed force and the flank wear land area are plotted in Fig. 12 for different cutting conditions. The experimental results prove that it would be very difficult to attempt to use the varying characteristics of the spectral peak value obtained from the Fourier transform as the determining parameters for monitoring the flank wear states. This result coincides with those from other studies^{(11),(12)}.

Based on the above experimental and analyzed results, a monitoring system for the flank wear states can be developed using the expansion coefficients $d(j, k)$. That is, first the feed force signals over a wide frequency band around the natural frequency of the tool vibratory system can be transformed and scaled

using the wavelet transform repeatedly five times. Next, the obtained sets of the expansion coefficients $d(j, k)$ are used to average the absolute values of $d(j, k)$. The average values $\bar{w}$ are classified according to the cutting conditions, and then used as recognition parameters of the tool wear states. Finally, the parameters are standardized and memorized in the monitoring system as a criterion.

The algorithm of the FWT is very simple and its implementation takes less time than the fast Fourier transform. According to our test calculation using an engineering workstation, the FWT of 1 024 data took 5.6 times less time than the fast Fourier transform. The monitoring technique using the wavelet analysis should be widely applied in machining fields.

4. Conclusions

Through the aforementioned analyses and discussions, the following conclusions can be made:

(1) The wavelet transform is proposed as a tool for monitoring the flank wear states. In this paper, the expansion coefficients $d(j, k)$, being capable of representing the multiresolution of cutting force signals, were used to extract the time-frequency features of the flank wear states from feed force signals.

(2) Based on the consideration of the natural frequency of the tool vibration system and the feature of the peak frequency shift of feed force with the development of tool wear, the expansion coefficients $d(5, k)$, which are located in the frequency zone from 3 200 Hz to 6 400 Hz, can be obtained by implementing FWTs five times.

(3) The average feature $\bar{w}$ of expansion coefficients $d(5, k)$ is sensitive to the flank wear and cutting conditions. The relationship between the average feature $\bar{w}$ and the flank wear land area is linear for a given feed rate and cutting speed and is independent of the depth of cut. Thus, the average feature $\bar{w}$ can reliably identify the tool wear states under different cutting conditions.

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