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IN SITU CHATTER FREQUENCY PREDICTION USING TORQUE DATA FROM A WIRELESS SENSOR INTEGRATED TOOL HOLDER

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ABSTRACT

A method is demonstrated to estimate chatter frequencies in real time from cutting torque data using formant frequency tracking. Formant frequencies are derived from the torque data using linear predictive coding (LPC) methods, similar to algorithms used in speech recognition. The estimated frequency response is observed to change throughout a cut as a function of both engagement and cut geometry. Torque data is collected at high bandwidth from a wireless sensor integrated end milling tool holder. The technique is found to be effective and repeatable for forecasting regenerative chatter frequencies in real time. Chatter frequencies predicted during non-chatter conditions correctly estimate the actual chatter condition. To demonstrate the technique, a number of experimental cuts are conducted and discussed.

INTRODUCTION

Prediction of chatter frequencies is essential for increasing material removal rates while maintaining acceptable machined surface quality. This is specifically pertinent for materials such as nickel based alloys, titanium, and steels where high speed machining may not be a practical option due to tool wear limitations. Ideal process planning solves this problem with stability lobe diagrams based on estimation of the machine tool frequency response function (FRF) [1,2]. Unfortunately, the estimation of stability becomes more difficult with the introduction of changing workpiece dynamics, bed and spindle position, and during low spindle speed operations. Regenerative chatter is a major limitation to the productivity and quality of machining operations due to the excessive rate of tool wear and scrap parts produced with poor surface quality. Typical machining chatter analysis techniques examine the stability of a closed-loop model (force process and machine tool-part structure) of the machining operation to determine the stable process parameter space.

In the words of [2], “Nothing is a better representation of reality than reality (actual cutting).” Although the literature [1,2,3,4] has presented elegant mathematical forms describing the physical dynamic system, it is impossible for any simulation to capture unforeseen variables, nonlinearities, and stochastic behavior that exist in a real machining system. Although both analytical and time domain solutions can offer coarse estimates of stable spindle speeds, small deviations in the estimated FRF result in significant error in the stable parameter space. This is a particular problem for low to medium speed machining. Therefore, a real time updating method based on cutting data can improve model-based prediction of stable cutting speeds as they change throughout a cutting process. Cutting data must be retrieved with sufficient resolution to detect subtle changes in frequency and magnitude response.

A commercially available system [5] uses a microphone placed in the vicinity of the cutting area to record audible frequencies. When chatter occurs, the specific chatter frequencies can be identified by filtering out the tooth passing frequency and its harmonics. This method is effective as long as chatter is present and there is minimal ambient noise to interfere with the signals of interest. In contrast, the method described in this paper is not susceptible to ambient noise and can identify chatter frequencies even when there is no perceptible chatter. Furthermore, our method is capable of detecting chatter frequencies with minimum computational burden, thereby enabling close to "real-time" chatter avoidance by shifting to safer spindle speeds.

By employing wireless techniques and embedded sensors, effects on system stability due to the tool-workpiece interaction can be more clearly observed [6,7]. This stability information can be updated throughout changing cutting conditions and may be used to operate a process with more aggressive material removal rates while avoiding stability issues, namely chatter or forced vibrations. In order to fully understand dynamic end milling problems such as regenerative chatter, it is necessary to observe the tool tip response characteristics as close as possible to their source.

SENSOR INTEGRATED TOOLING SYSTEM

The sensor system used for this work is a torque sensing tool holder with a streaming bandwidth of 10.24 kHz at 16 bit resolution. The amplifier and transmitter circuits for the integrated tooling system are mounted on the external surface of a CV40 set screw type tool holder (Figure 1). Sensors made from semiconductor strain gages are used to sense torsional shear on the tool holder body. Because these sensors provide a gage factor of approximately 120, the stiffness of the tool holder is not compromised for resolution. A Lexan shield protects the electronics from impact and fluid. Figure 1 shows the tool holder with the amplifier circuit in the shield. For further clarity, video demonstrations of the device in operation are made available at [8] and on Google Video under the keyword "smart tool holder".

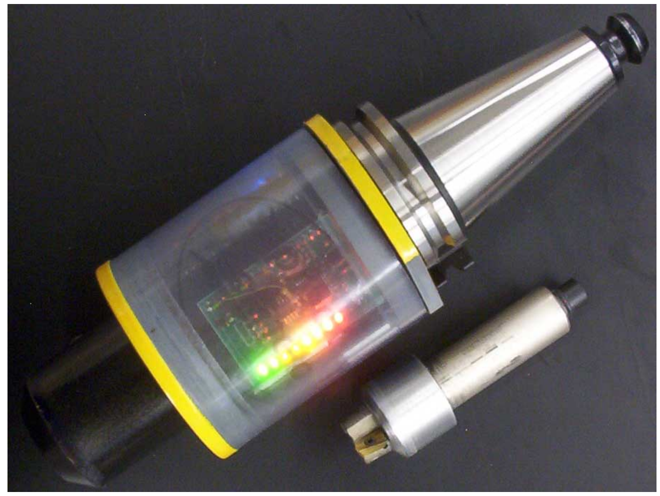

Figure 1. Torque Sensor Smart Tool

To minimize phase effects in the data, no data compression protocols were deployed in the system. The Bluetooth serial transmitter conforms to the published specifications in [9]. The analog signal conditioning circuit on this particular transmitter has a high frequency roll off with a corner frequency below 5 kHz to prevent aliasing in the digital signal. The effective frequency bandwidth of this transmitter is approximately 0 Hz to 5 kHz.

MATHEMATICAL BACKGROUND

The torque data captured by the sensor integrated tool reflects the instantaneous chip thickness during cutting. This signal contains both tooth passing and the dynamic chip thickness components. The dynamic chip thickness is the result of the machine tool system dynamics. The torque data can be approximated as the output from a LTI (linear time invariant) system with the time domain torque signal equal to the periodic chip thickness input signal convolved with the frequency response function (FRF) of the system. This is defined in the time domain as:

$$\tau(t) = p(t) * f(t) \tag{1}$$

and in the frequency domain as:

$$T(s) = P(s) \cdot F(s) \tag{2}$$

where p is the tooth passing chip thickness signal (input), f is the frequency response function, and τ is the output torque signal from the sensor data. Linear Predictive Coding (LPC) methods are used to estimate the locations of system poles in F(s). The complete system transfer function F(s) could be determined using LPC if the input p(t) was white noise. In reality, the chip thickness input is a periodic signal at the tooth passing frequency. This provides significant frequency content to excite the system (see Figure 8) so that the major poles can be located, but it does not allow us to determine the complete transfer function. In cases where the frequency content of the input signal is limited, the poles of the system may be difficult to determine.

Linear Predictive Coding and Formant Frequency Tracking

Linear predictive coding is a method of creating a model spectrum from a discrete waveform to capture the spectral shape of a data set while disregarding detailed harmonic structures [10,11]. In a traditional example, it is used to estimate the formant frequencies of lung-mouth-nasal systems for human speech recognition. We propose to use the method to determine the dominant vibration modes in the torque signal obtained from the smart tool during a cut. In an end milling system, significant tooth passing harmonics exist throughout the torque spectrum T(s). LPC provides a method to distinguish the significant system poles from the harmonics of the tooth passing frequency.

The autocorrelation method of LPC chosen for this work is detailed in [11]. Assuming for a given window of τ and model order *M,* the present sample is predicted by autoregressing the historical samples of torque data:

$$\tilde{\tau}=a_1\tau(n-1)+a_2\tau(n-2)+...+a_M\tau(n-M) \\ =\sum_{i=1}^{M} a_i\tau(n-i) \tag{3}$$

where τ is the prediction of τ(n), τ (n-i) is the i^{th} step historical sample, and $\{a_i\}$ are linear coefficients. The sum of squared prediction error takes the form:

$$E=\sum_n \epsilon(n)^2=\sum_n(\tau(n)-\tilde{\tau}(n))^2 \\ =\sum_n\left(\tau(n)-\sum_{i=1}^{M}a_i\tau(n-i)\right)^2 \tag{4}$$

By minimizing SSE, E , it is feasible to solve for the prediction coefficients $\{a_i\}$ by setting the derivative of E with respect to $\{a_i\}$ equal to zero:

$$\sum_n 2\tau(n-k)\left(\tau(n)-\sum_{i=1}^{M}a_i\tau(n-i)\right)=0 \tag{5}$$

for $k=1,2,\ldots,M$

This form contains *M* unknowns and *M* equations:

$$\sum_n\tau(n-k)\tau(n)=a_1\sum_n\tau(n-k)\tau(n-1)+... \\ ...+a_2\sum_n\tau(n-k)\tau(n-2)+...+a_M\sum_n\tau(n-k)\tau(n-M) \tag{6}$$

Assuming that there is a finite number *N* of discrete samples in the data window τ , Equation 6 can be approximated in Yule Walker matrix form :

$$\begin{bmatrix} r(0) & r(1) & \ldots & r(M-2) & r(M-1) \\ r(1) & r(0) & \ldots & r(M-3) & r(M-2) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ r(M-2) & r(M-3) & \ldots & r(0) & r(1) \\ r(M-1) & r(M-2) & \ldots & r(1) & r(0) \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_{M-1} \\ a_M \end{bmatrix} \begin{bmatrix} r(1) \\ r(2) \\ \vdots \\ r(M-1) \\ r(M) \end{bmatrix}^T \tag{7}$$

or $Ra=r$, recalling that *{r(1)...r(M)}* is an autocorrelation estimate for τ :

$$r(k)=\sum_{n=0}^{N-1-k}\tau(n)\tau(n+k) \tag{8}$$

The matrix form of Equation 7 is solved with the Levinson-Durbin recursive method to minimize the required computation to solve $\{a_i\}$. This algorithm is described fully in [11, 12 ,13]. Once the coefficients $\{a_i\}$ are solved, the roots of the model can be found. The poles of the system frequency response function, F(s), are estimated by treating the model as an all-pole (infinite impulse response) IIR filter:

$$F(z)=\frac{1}{A(z)}=\frac{1}{1+a_2z^{-1}+...+a_{n+1}z^{-n}} \tag{9}$$

The location of system poles can be estimated in real time from a window of the experimental cutting torque data, τ. The set of system poles, *R*, are found as the polynomial roots of the filter denominator (Equation 9).

Formant frequencies are calculated by the phase angle of the system poles and scaled by the discrete sampling frequency of τ:

$$Fr=\frac{\measuredangle R}{2\pi(Fs/2)} \tag{10}$$

where *R* are the system poles, *Fs* is the discrete sampling frequency of τ, and *Fr* is in units of Hz.

For the LPC method, it is important to note that we assume our data is both linear and time invariant over a short data window. However, a system that is not assumed to be time-invariant can be solved using other approaches such as the Green function method [14].

EXPERIMENTAL VALIDATION

Impulse Response Testing Provides a Baseline Machine FRF

Several experimental tests are presented to demonstrate the efficacy of the formant tracking method. The first experiment establishes the baseline "static" FRF of the end milling system using the traditional 'hammer test' in X and Y linear directions. The impulse response is measured with a piezoelectric accelerometer mounted to the milling tool. The tool is struck by a modally tuned hammer and both input and output response is recorded, as detailed in [1,2]. The FRF is estimated as the transfer function between the input and output signals, computed at each discrete frequency. Both X and Y axes are examined independently.

It is important to have this baseline to validate and contrast estimated system poles with those observed in F(z). Although it is not expected that these baseline FRF's will exactly match the in-cut results, they should corroborate the shape and location of system modes. The baseline FRF's are a 'static' (non-rotating and non-cutting) representation of the tool, spindle and machine structure, without workpiece dynamics. Moreover, the spindle is treated as a cantilever, free from engagement with the workpiece material. Figure 2 illustrates the baseline FRF for both X and Y directions.

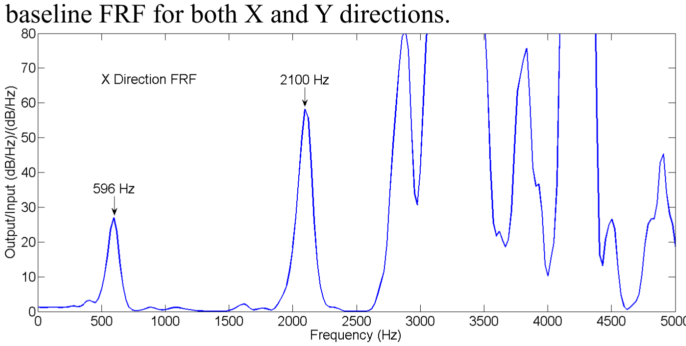

Figure 2A. Baseline Machine Tool FRF for X Direction

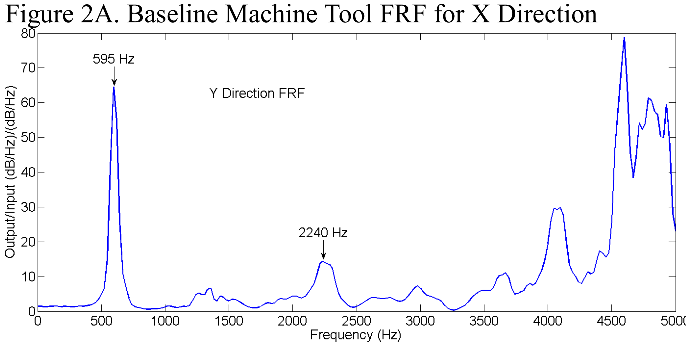

Figure 2B. Baseline Machine Tool FRF for Y Direction

From analyzing the baseline FRF's, two modes are observed to be likely candidates for chatter frequencies. At approximately 595 Hz, a natural frequency occurs in both X and Y directions. This mode is attributed to the cutting tool compliance which we anticipated to be the most compliant part of the machining system. The second mode may be the result of machine spindle dynamics. The first mode of the system is similar (~595 Hz) for both X and Y directions. The second mode has slight variation between X and Y (2100 vs. 2240 Hz). Frequency content above 2500 Hz for the X direction, and 3500 for Y, is not considered reliable.

Application of LPC Methods to Estimate an In-Cut System Poles

A slot cutting test at 45 degrees in the x-y plane is designed to excite the machine system in X and Y directions (see Figure 3). The chatter frequency (or frequencies) are expected to occur near the lowest modes of the system. Recalling that our goal is to estimate the system chatter frequencies from the torque data *before encountering chatter*, the test is run with a shallow axial engagement. Moreover, the test is conducted in a solid clamp-anchored workpiece to minimize the influence of workpiece dynamics. The test conditions are 2501 RPM, axial depth 3.81mm (0.15 inch), at a feed rate of 254 mm/min (10 ipm). The cutting tool selected for this test was a Kennametal Mill 1-10 with a 19.05mm (0.75 inch) cutting diameter.

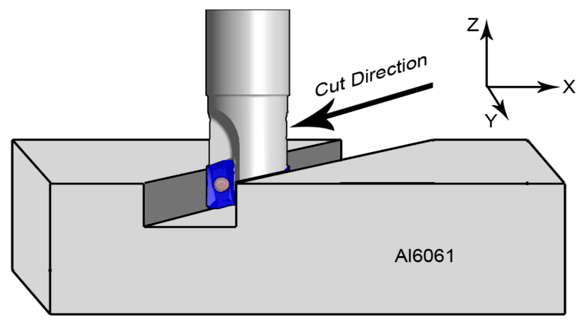

Figure 3. XY Slot Cutting Experimental Orientation

The torque data collected for this test is shown in Figure 4. No chatter build up was encountered and the workpiece finish remained acceptable. The torque magnitudes are comparable to theoretical estimations from an infinitely stiff mechanistic cutting force model. It should be noted that no run out was present since a single insert cutter was used for the test.

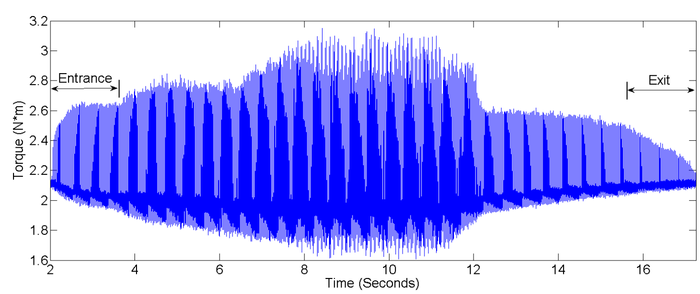

Figure 4. Torque Plot from the XY Slot Cut

From this torque data, Equations 4 through 11 are used to generate a set of formant frequencies locating the peaks of the estimated system poles. Figure 5 shows Equation 11 evaluated for a 10 pole model (the four higher formant frequencies shown). These formant frequencies track possible chatter frequencies throughout the cutting process, updated at each window of τ . Each window contains 1024 data points collected at 10.24 kHz.

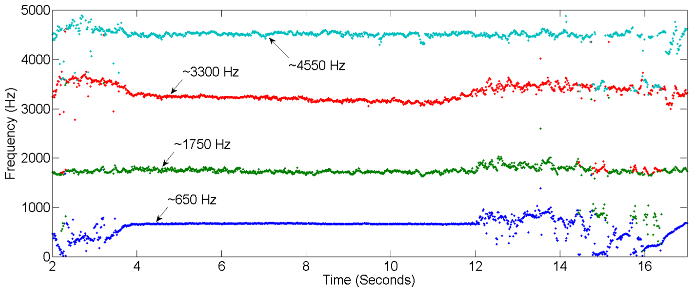

Figure 5. Dominant Formant Frequencies of the XY Slot Cut

Formant frequencies represent the peak magnitude locations in the model frequency response. It is observed that the estimated system FRF (poles only) , $F(z)$, aligns with dominant modes in the baseline FRF's (Figure 2). However, the estimated poles occur at slightly different frequencies from those observed from the baseline impulse response test. Figure 6 shows a 10th order (five pole) model of the system, estimated from the cutting torque signal, τ . Figure 6 was generated with the MATLAB Filter Visualization Tool, treating the estimated FRF as an IIR filter.

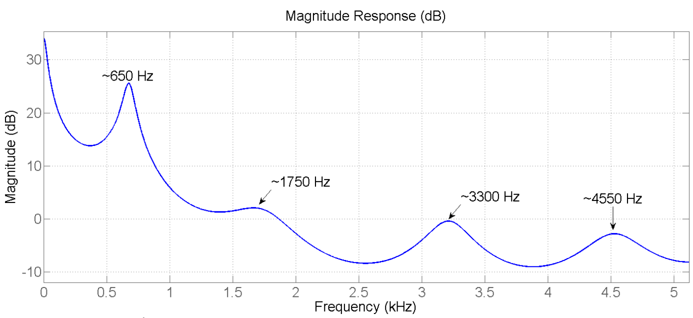

Figure 6. 10th Order Model Frequency Response From Cutting Torque Data

A reader may question the validity of the 10th order model, without a discussion of minimally sufficient model order. Therefore, a 64th order model is presented for the same data window as Figure 6. Based on this comparison, it is evident that there is no substantial improvement in frequency resolution of the estimated poles. However, there is an arguable improvement on the resolution of the second dominant mode, recalling that there are two distinct frequencies for the X and Y transfer functions shown in Figure 2. Figure 7 shows the 64th order model FRF.

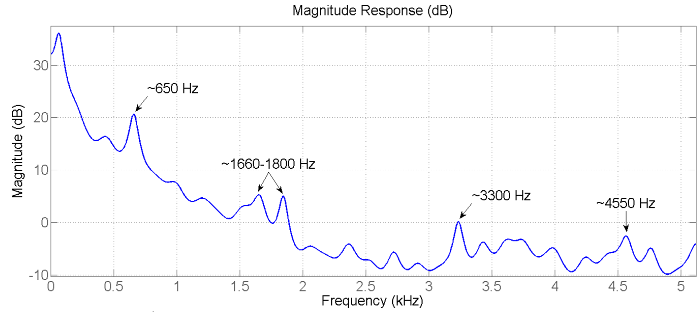

Figure 7. 64th Order Model Frequency Response From Cutting Torque Data

Figure 8 shows the power spectrum of the raw torque data, τ , for the stable cut at 3.81mm (0.15 inch) axial depth. Unlike the model spectrum, the raw spectrum is dominated by tooth passing harmonic frequencies and is difficult to interpret to determine the location of system poles. By comparing Figure 8 to Figures 6 and 7, it is clear that the LPC method is smoothing the frequency response such that tooth passing harmonic frequencies are eliminated while preserving the system's overall response shape. Specifically, the system shape is not readily apparent in Figure 8.

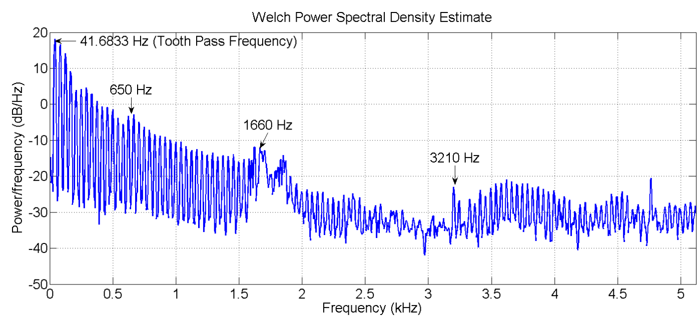

Figure 8. PSD of Stable (no chatter) Raw Torque Data

Observation of Time Varying Effects on Model FRF and Predicting Stable Cutting Speeds

Because the system frequencies are estimated from the streaming torque data, time varying effects in the modes can be observed. An interesting phenomenon is drift captured in the formant frequencies during steady state cutting. This suggests that the modes of the system may be shifting frequency throughout the cutting process. Figure 9 shows the lowest formant frequency from Figure 5, corresponding to the ~650 Hz mode of the cutting tool. This mode is observed to drift within a 15 Hz envelope of its mean value. This effect is fascinating and warrants further investigation.

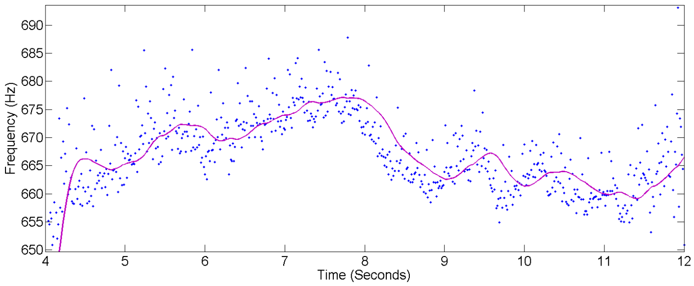

Figure 9. Drifting System Poles During Steady State Cutting

The literature [2] describes difficulties in accurately predicting stable spindle speeds at low RPM. The drift we observe in the in-process FRF may contribute to this difficulty. At low spindle rpm, the stable parameter space is highly sensitive to small variations in the chatter frequency, ω_c. For this reason, estimating the in-process FRF poles is critical to maintaining stability at low spindle speeds. Assuming that the chatter frequency is very close to a system natural frequency (determined from the in-process FRF), it is possible to predict the peaks of the unstable modes in a stability lobe plot. By understanding the relationship between phase shift and spindle frequency, the locations of peak instability can be determined according to the peak phase shift of the structural transfer function [1]. This phase shift can be calculated by:

$$\psi = \tan^{-1}\left(\frac{\sin(\omega_c T)}{1-\cos(\omega_c T)}\right) \qquad (11)$$

Where T is the tooth passing period and ω_c is the chatter frequency in rad/s. Evaluating this function over a range of spindle speeds identifies the least stable speeds at the peak values of ψ. A peak-trough plot of instability can be computed by:

$$|\kappa| = |\tan(\psi)| = |\tan(\pi/2 - \omega_c t)| \qquad (12)$$

In other words, the most stable cutting speeds occur at the minimum values of Equation 12. By evaluating Equation 12 using the formant frequencies predicted by Equation 10, a set of 'safest' spindle speeds can be generated from each data window of τ. This is a key point to note from this work and opens the door for future work involving control implementations.

A sensitivity analysis of Equations 11 and 12 demonstrates the severity to which stability can be affected when T is relatively large (i.e. in regimes under 10,000 RPM). Referring to [1,2] the full stability lobe diagram can be computed when the full FRF of the system is known.

Validating the System Frequencies by Inducing Chatter

Finally, the validity of the model FRF poles is tested by conducting an identical cut at an increased axial depth of 7.62 mm (0.3 inches). By increasing the axial depth, chatter is induced and the actual chatter frequency can be observed. The true chatter frequency is observed in the power spectrum of the raw torque data at 650+-10 Hz, plotted in Figure 10.

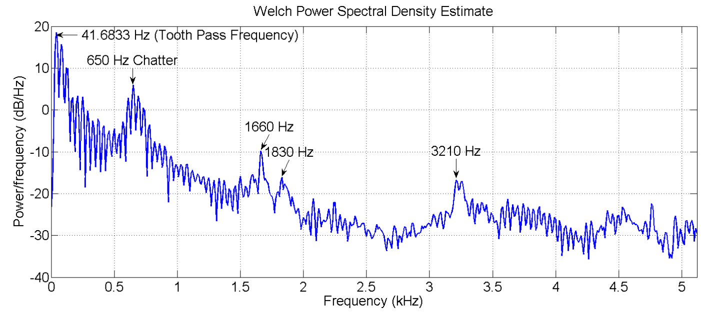

Figure 10. PSD of Raw Torque Data Under Induced Chatter

Based on the experimentally obtained results, the LPC model FRF low frequency mode of 650 Hz matches the significant chatter frequency shown in Figure 10. The results of the tap tests, i.e. the baseline FRF's, give little indication of the chatter frequency. Obviously, because of the more accurate chatter frequency prediction, the LPC model would give better estimation of stable spindle speeds for safe cutting.

Changes in the Model Poles as a Function of Spindle Speed

With an in-process estimation of the FRF poles, a feedback control mechanism can be developed to adapt machine tool process parameters in response to predicted chatter conditions. For this reason, it is important to understand the effect of machine tool process parameters on the accuracy of the FRF estimation method. Because spindle speed is a control variable with respect to machine tool stability, its effect on the chatter frequency is an interesting topic. To explore this, a suite of slot cutting tests is repeated at two axial depths of cut. The first depth, 2.54 mm (0.1 inches), is intended to test the ability of the prediction method to forecast the chatter frequency without encountering a tool chatter condition. The second depth, 7.62 mm (0.3 inches), is designed to induce regenerative chatter and validate the chatter frequency predictions made from the first depth. Figure 11 is a conceptual model of the experimental setup for this test.

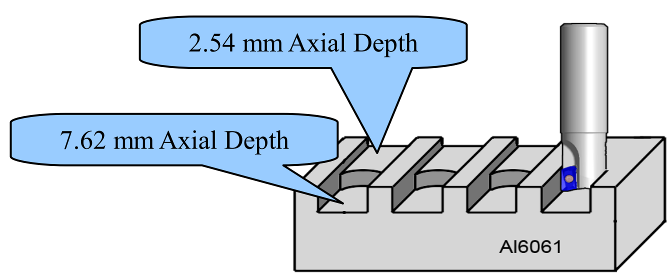

Figure 11. Multi-Depth Slot Cutting Experimental Orientation

The outcome of these tests further validates the ability of the LPC method to estimate the correct mode locations from the cutting torque data. In all cases, the chatter frequency is estimated as the lowest formant frequency from the model FRF. Table 1 shows the predictive (2.54 mm depth) versus the induced chatter frequencies as a function of spindle speed.

	Spindle Speed (RPM)						
Axial Depth	2501	2750	3000	3250	3500	4250	4750
2.54 mm (0.1”)	649	664	673	675	678	686	693
7.62 mm (0.3”)	655	667	679	683	679	686	680

Table 1. Predicted and Actual Chatter Frequencies as a Function of Spindle Speed for Slot Cuts

Plotting the induced chatter frequencies over the range of spindle speeds produces a nonlinear relationship. This may be the effect of changing bearing stiffness, damping, or inertial effects. More investigation is necessary to explore this phenomenon. Unquestionably, this effect is not captured by traditional impulse response testing of the spindle and is an important clue to correctly modeling the system. Although the change in chatter frequency is within 30 Hz, system stability is highly influenced by small changes at low spindle speeds. Figure 12 shows the relationship between observed chatter frequencies and spindle speed. A quadratic fit is made to the data trend. Although not fully understood, the literature [18,19,20] documents that the FRF does change as a function of spindle speed, affecting stability estimation and increasing the difficulty of selecting stable process parameters.

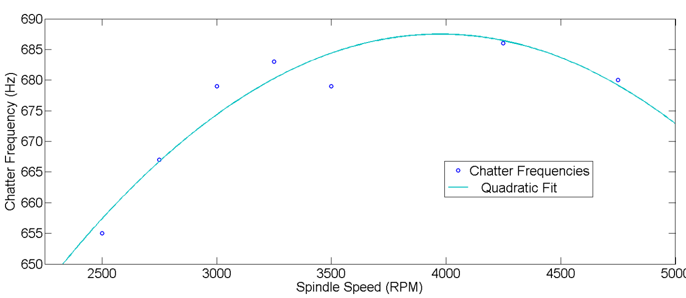

Figure 12. Chatter Frequencies vs. RPM

Estimating the System Poles in Partial Engagements

To this point, we have discussed examples of estimating an in-process chatter frequency based on torque data from various slot cutting scenarios. It is also necessary to demonstrate the method for partial engagement cutting. To do so, partial radial immersion cuts were conducted at 4.7625 mm (0.1875 inch) radial depth. Figure 13 is a conceptual model of the experimental setup for this test.

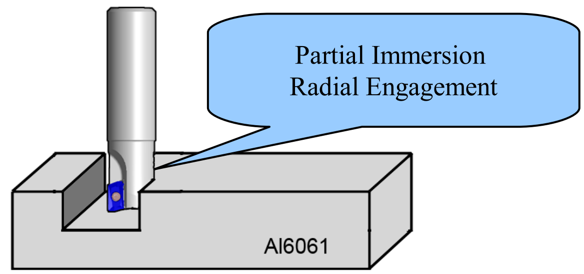

Figure 13.Quarter Radial Immersion Experimental Orientation

For the ¼ immersion cutting experiments, the model shows poles that are present in the baseline FRF (obtained by the hammer test), occurring at slightly shifted frequencies (see Figure 14). Unlike the slot cutting examples, this system does not chatter in radial immersions under 9.5250 mm, regardless of axial engagement. This was observed for both up milling and down milling experiments. However, despite the inability to produce chatter at light radial engagement, the estimated system natural frequencies reflect those obtained from the slot cut. While poles can be determined from the ¼ immersion cut as shown in Figure 14, it is much more difficult to select a dominant natural frequency at 670 Hz. More experiments are needed to determine the cutting conditions necessary to accurately determine the dominant system poles.

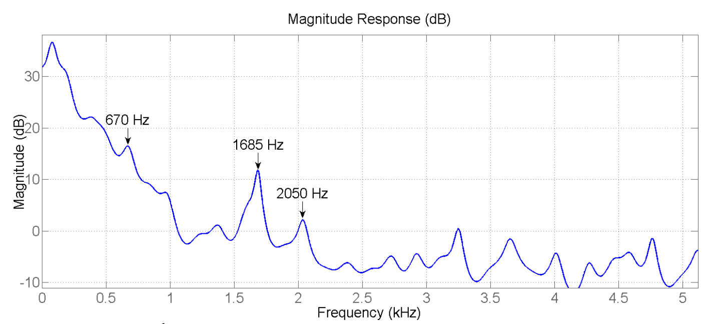

Figure 14. 64th Order Model Frequency Response From Quarter Radial Immersion Cutting Torque Data

CONCLUSIONS

The machining system FRF poles, and hence natural frequencies, can be estimated from cutting torque data collected from a wireless sensor integrated end milling tool holder. Using LPC methods, this model FRF can be estimated in real time from windows of cutting data. It is shown experimentally that unstable chatter frequencies can be observed from the LPC model during highly stable cutting conditions. This is an exciting advance from traditional methods that estimate chatter from the impulse response of the machine, particularly for low spindle speeds where stability becomes highly sensitive to changes in the chatter frequency. The ability to exploit formant frequency tracking to follow changes in the system modes and hence chatter frequencies has also been demonstrated. The techniques are computationally efficient since low model orders provide sufficient system resolution, processing in under a millisecond per data window on a modest PC laptop. The ability to predict unstable frequencies from highly stable cuts is beneficial to ad-hoc process planning and adaptive adjustment to the process parameters.

FUTURE WORK

Future work involves more experimental testing to evaluate the use of LPC methods to track system poles for many different cut geometries and materials. Other work involves direct application of these techniques for in-process frequency tracking as well as real-time estimation of stable spindle speeds for in situ process planning. The algorithms are being implemented on 32 bit microcontrollers, taking advantage of integrated DSP abilities. The algorithms presented will be integrated with the wireless sensor integrated tool holder so the device will actively suggest changes in spindle speed corresponding to updated stability calculations. In addition to the application of LPC techniques, extended Kalman filters (EKF) are being investigated for real time state estimation and frequency tracking.

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