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Letter to the Editor

Chatter recognition by a statistical evaluation of the synchronously sampled audio signal

Tony L. Schmitz*

Manufacturing Metrology Division, National Institute of Standards and Technology, 100 Bureau Drive, MS 8223, Gaithersburg, MD 20899, USA

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1. Introduction

Milling is a complex dynamic process that includes periodic impacts of the cutting teeth with the workpiece, corresponding vibrations of the cutter and workpiece that define the machined surface, and overcutting of the surface left by previous teeth by the current tooth. The removal of the undulating surface produced by the preceding tooth with the current tooth is referred to as *regeneration of waviness* and is a primary source of instability in milling [1]. Regeneration of waviness leads to a variable chip thickness and, therefore, variable cutting force which causes, in turn, vibrations of the tool and workpiece. This closed-loop feedback of force and vibration provides the mechanism for self-excited vibration, or chatter. Depending on the selected chip width (for a particular dynamic system, cutter geometry, and workpiece material), the subsequent vibrations of the cutter can diminish for stable cutting, or increase to some bounded limit for chatter. A schematic representation of a 50% radial immersion down-milling operation is shown in Fig. 1.

Because the variable cutting force can become large and the machined surface quality is poor, it is desirable to avoid unstable milling conditions. An important analytic tool that has been developed to aid in the selection of stable cutting parameters is the stability lobe diagram [2–6]. These diagrams allow the user to select appropriate combinations of the control parameters, chip width and spindle speed, by separating stable from unstable regions with the analytic 'lobes'; see Fig. 2. The construction of these diagrams requires pre-process knowledge including the tool point frequency response function, expected radial immersion, and specific cutting energy coefficients that depend on the workpiece material, tool geometry, and cut parameters.

In many instances, the calculation of optimum milling conditions using stability lobes diagrams for each tool/holder/spindle/machine/material combination on the shop floor is not possible due

*Current address: Department of Mechanical and Aerospace Engineering, University of Florida, Gainesville, FL 32611-6300, USA.

E-mail address: tschmitz@ufl.edu (T.L. Schmitz).

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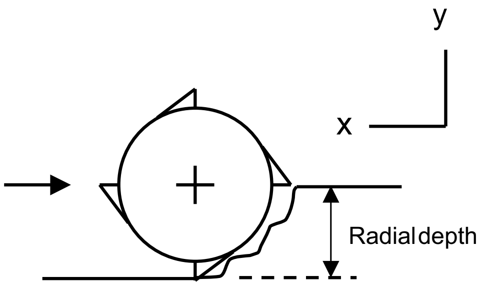

Fig. 1. Fifty per cent radial immersion milling schematic; cutter rotation is clockwise.

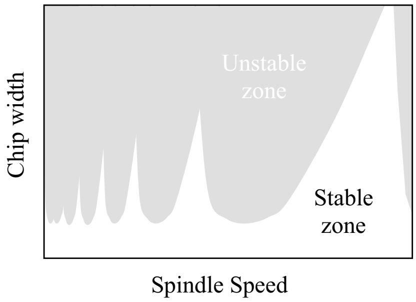

Fig. 2. Example stability lobe diagram showing separation between stable and unstable cutting conditions as a function of allowable chip width and spindle speed.

to inadequate engineering support. In these situations, the need to rapidly identify stability behavior using methods that do not require an extensive background in vibration theory increases. One available pre-process option is the Harmonizer™ system [7] that calculates the fast fourier transform (FFT) of the time-based audio signal collected during unstable milling.[1] The resulting spectrum is comb filtered to remove the tooth passing frequency and higher harmonics. The dominant chatter frequency, f_c (in Hz), can then be identified from the filtered spectrum and the most stable spindle speeds selected according to Eq. (1), where Ω_j is the spindle speed (in revolutions/min or r.p.m.) corresponding to the jth lobe, j is the integer lobe number, and N_f is the number of flutes on the cutter:

$$\Omega_j = \frac{60 f_c}{j N_f}, \quad j = 1, 2, 3 \ldots . \tag{1}$$

Although the in-process method described here does not offer the diagnostic capability of identifying alternate stable spindle speeds without additional signal processing, it does sense chatter using a much less computationally intensive procedure, i.e., a simple statistical interrogation of the time-based signal versus the frequency-domain FFT and subsequent filtering, and operates on a much smaller data set. Specifically, only one sample per spindle revolution is

[1] Commercial equipment is identified in order to adequately specify certain procedures. In no case does such identification imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the equipment identified is necessarily the best available for the purpose.

required versus the tens of kiloHertz sampling rates necessary to avoid aliasing in the FFT analysis. Additionally, it is not necessary to analyze the entire frequency spectrum within the selected bandwidth to search for and identify any offending chatter frequencies; it is only required that a single scalar quantity, the variance in the synchronously sampled cutting data, be considered. These benefits make it a prime candidate for real-time, remote condition-based monitoring of milling process stability. Other efforts in the general area of condition-based monitoring of machines and structures include both time and frequency domain techniques. Example references are included for further reading [8–16].

2. Theory

The notion of a statistical evaluation of the once-per-revolution milling audio signal to detect chatter is based on Poincaré mapping techniques, where a local description of transient behavior is constructed from the Poincaré map and the system stability may be established [17]. For milling, the stability can be evaluated by plotting the x direction versus y direction tool motions and identifying the once-per-revolution sampled data points [18]. For stable cutting, the synchronously sampled points approach a fixed point for the Poincaré map after some initial transients and, thus, provide a tight distribution. Physically, this means that, although the tool is vibrating in the two orthogonal directions, the motions are synchronous with spindle rotation and the tool is returning to approximately the same position in each revolution under steady state conditions. In contrast, tool motions during regenerative chatter are not synchronous with spindle rotation; instead, they occur near the natural frequency corresponding to the most flexible system mode due to the nature of self-excited vibrations. For these unstable cuts, the tool does not return to the same position each revolution. Rather, the once-per-revolution sampled distribution can tend toward an elliptical shape due to the quasi-periodic nature of chatter. The two cases are shown in Figs. 3 and 4. In both instances, simulated x and y direction tool motions, as well as the

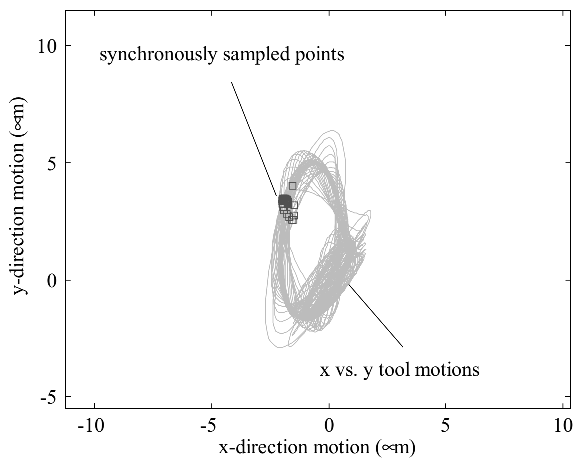

Fig. 3. Fifty per cent radial immersion stable cutting example.

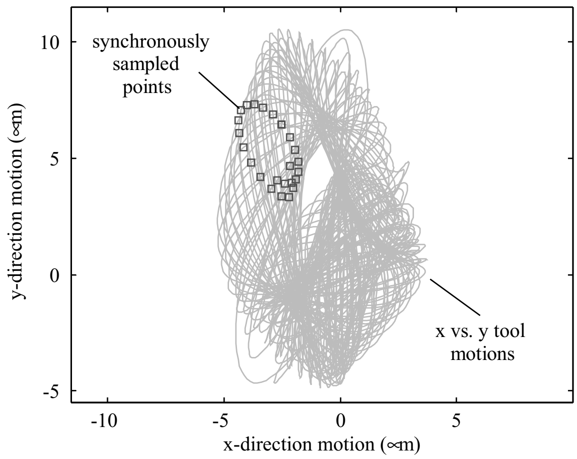

Fig. 4. Fifty per cent radial immersion unstable cutting example.

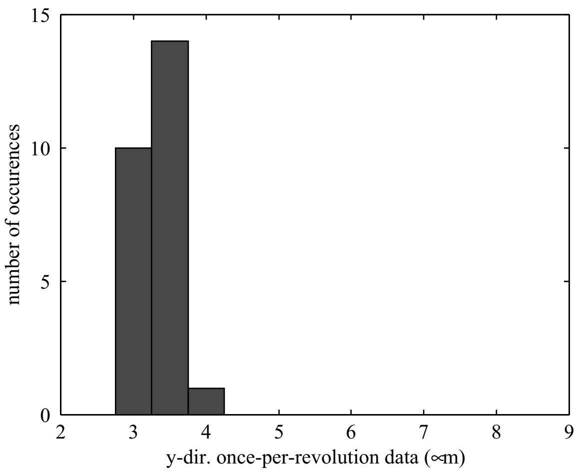

Fig. 5. Histogram of once-per-revolution points for stable 50% radial immersion cut.

synchronously sampled data pairs, are plotted for a 50% radial immersion down-milling operation. In Fig. 3, the axial depth of cut (i.e., the chip width or cutting depth along the tool axis for end milling) is below the critical limit and stable cutting is observed. In Fig. 4, however, the axial depth is above the critical limit and chatter occurs. Figs. 5 and 6 show histograms for the synchronously sampled y direction tool motions in Figs. 3 and 4, respectively. It is clear that the two distributions differ dramatically with the stable cut showing a tight distribution and the unstable cut a wider spread.

Given the different distributions for the synchronously sampled data, it is possible to distinguish between stable and unstable cutting conditions using only a once-per-revolution process signal with adequate signal-to-noise ratio and some performance metric. In this study, the selected metric was the variance in the synchronously recorded milling audio signal [19]. Variance was selected because it provides a measure of the spread in a sample distribution. The variance, σ^2,

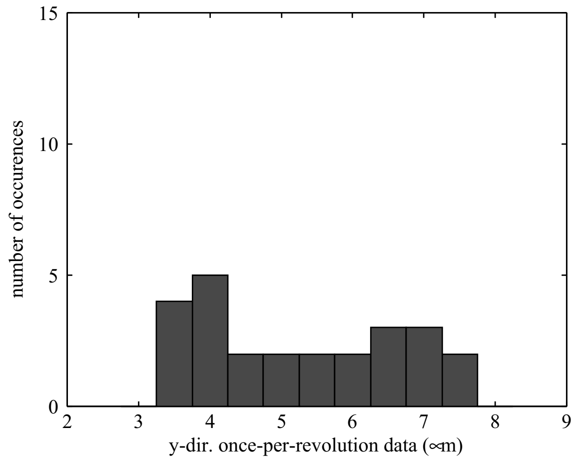

Fig. 6. Histogram of once-per-revolution points for unstable 50% radial immersion cut.

of the sample distributions consisting of N values, x_i, was calculated according to Eq. (2), where x_m is the mean or arithmetic average of the samples [20]:

$$\sigma^2 = \frac{\sum_{i=1}^{N}(x_i - x_m^2)}{N-1}, \quad \text{where} \ \ x_m = \frac{\sum_{i=1}^{N} x_i}{N}. \tag{2}$$

The decision to use the milling audio signal, obtained by placing a unidirectional microphone in the machine tool enclosure during machining was based on several considerations [21]. First, it is possible to place the sensor in reasonable proximity to the process. This limits the filtering effects of components between the process and sensor (e.g., distortion of the cutting signal by the machine tool structure before it reaches a remotely placed vibration sensor). Second, only one sensor is required to fully diagnose the process stability. Third, improved sensitivity to chatter in situations of low force or radial immersion compared to force-based sensors has been demonstrated [21].

3. Experimental results

In this section, a description of the experiment set-up and cutting tests parameters is provided. This is followed by the analysis methods applied to the milling audio signal. The methods include recording the once-per-revolution audio signal using: (1) an infrared emitter/detector pair, (2) the actual spindle speed, and (3) the commanded spindle speed. The latter two were explored in an effort to simplify the test set-up.

3.1. Set-up

The experimental set-up for implementation of the audio signal variance condition-based monitoring for milling process stability is shown in Fig. 7. The required hardware, which was mounted on a high-speed, horizontal spindle (20 000 r.p.m./20 kW) machining center, included a unidirectional microphone (Optimus 33-3023[1]) mounted inside the machine enclosure,

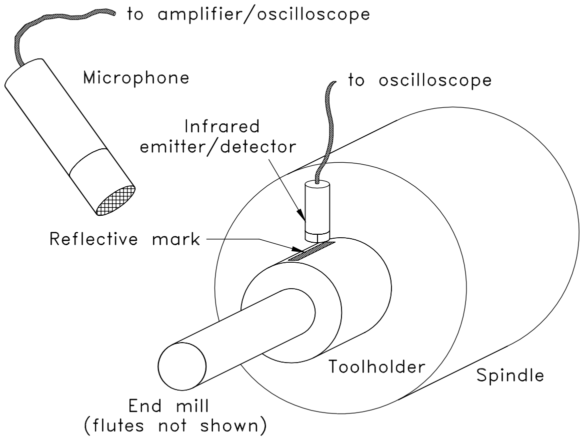

Fig. 7. Set-up for cutting tests showing microphone and infrared emitter/detector pair.

microphone amplifier (PCB 482A17[1]), once-per-revolution signal generator comprised of an infrared emitter/detector pair and reflective tool mark, and a digital oscilloscope for collection of the time-based audio and once-per-revolution signals.

A preferred set-up for industrial applications would include use of the microphone and access to the spindle encoder's once-per-revolution signal to trigger audio data collection, employing available data acquisition channels in the machine tool controller or a data acquisition card in a local computer with network connections. This once-per-revolution data could then be represented in a local and/or remote real-time display that includes the instantaneous variance value and a continuously updated histogram, similar to the frequency-based LED output seen in various stereo equalizers [22], to indicate the process stability. The identification of chatter using data represented in this manner would require no knowledge of the machine dynamics, specific cutting energy coefficients, process parameters, or vibration theory and could potentially provide condition-based monitoring capabilities for stability of milling processes.

The 50% radial immersion down-milling cutting tests were performed using a 12.7 mm diameter, two flute, helical carbide end mill with a 44 mm overhang. The workpiece material was selected as 6061-T6 aluminum, although other materials could also be chosen. Twenty-five cutting tests were performed covering spindle speeds from 14 000 to 18 000 r.p.m. (1000 r.p.m. steps) and axial depths from 2.03 to 5.08 mm (0.76 mm steps). In all cases, a constant feed per tooth of 102 μm was maintained. The microphone and once-per-revolution data were obtained using the set-up shown in Fig. 7. The microphone signal was analog low-pass filtered at 7 kHz and both the microphone and once-per-revolution signals were collected using a sampling frequency of 50 kHz.

3.2. Analysis

The first analysis method applied to the audio milling signal was to calculate the variance in the once-per-revolution values obtained using the infrared emitter/detector pair. The variance value in mV^2 for each cutting test (i.e., each spindle speed/axial depth combination) is shown in Fig. 8. A dramatic increase in variance of 48 to 709 mV^2 is seen for the transition from 2.79 to 3.56 mm axial depth at 15 000 r.p.m. Larger depths of 4.32 and 5.08 mm also show increasing variance

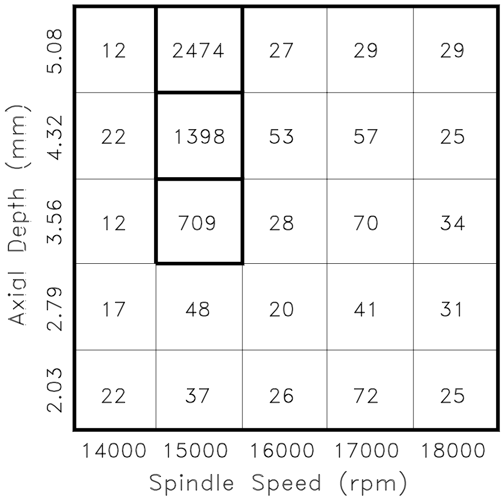

Fig. 8. Variance values in mV^2 for cutting tests using emitter/detector pair once-per-revolution trigger.

values. These large values indicate an increase in the spread of the data and identify unstable cutting conditions (the unstable cuts are denoted by the heavy grid lines in Fig. 8). All other spindle speed/axial depth combinations are stable, exhibiting small variance values. These results agree with independent evaluations of the process stability including surface finish measurements of the machined workpiece using a scanning white-light interferometer and FFT-based analyses of the milling audio signal (descriptions of the FFT analysis method are provided in Refs. [23–25]).

In condition-based monitoring applications, it is generally preferred to simplify the architecture of the sensor(s) and required hardware as much as possible to improve the monitoring system robustness [26]. Toward that end, the next analysis technique applied was to calculate the variance in the once-per-revolution values obtained using the actual spindle speed to generate an artificial once-per-revolution trigger, rather than the infrared emitter/detector pair. For this situation, the only hardware required is the microphone; however, the actual spindle speed must also be determined by some method, most likely using the spindle encoder signal.

For our purposes, the actual spindle speed was determined using the infrared emitter/detector signal. The FFT of the emitter/detector signal was calculated and the frequencies of the fundamental and first five harmonics (the impulsive once-per-revolution signal generates multiple harmonics with significant amplitudes) were recorded. The actual spindle speed was calculated from the average speed predicted by the six frequencies in order to reduce the effect of sampling errors (e.g., leakage):

$$n_r = \frac{60}{\Omega} f_s. \tag{3}$$

The time-based microphone data were then analyzed by calculating the number of samples per spindle revolution, n_r, from the actual spindle speed in r.p.m. and the digital sampling frequency, f_s, of 50 kHz (Eq. (3)) and using this value to periodically sample the vector of sound pressure amplitudes previously recorded by the unidirectional microphone. Because n_r was not, in general, an integer value, it was necessary to linearly interpolate between adjacent samples. For example, a

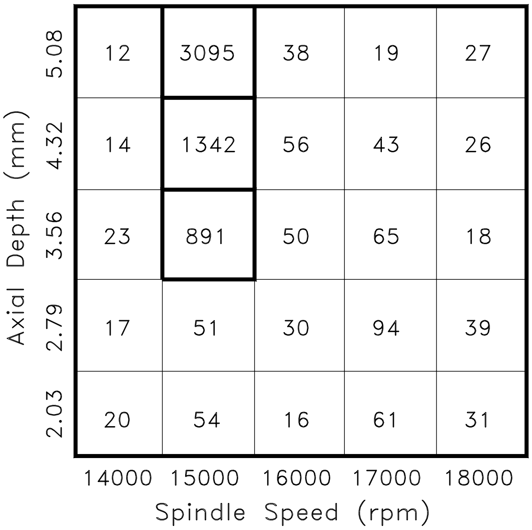

Fig. 9. Variance values in mV^2 for cutting tests using synthetic actual spindle speed once-per-revolution trigger.

spindle speed of 16 000 r.p.m. sampled at 50 kHz gives 187.5 samples/revolution. This would require sampling the microphone signal at index values of 187.5, 375, 562.5, 750, etc., or some similar combination. Since it is not possible to record index number 187.5, an approximate value was obtained by interpolating between values number 187 and 188. The variance values for the 25 cutting tests are shown in Fig. 9. Similar results to those shown in Fig. 8 are seen.

The final procedure employed to analyze the microphone signal was to use the nominal spindle speed directly to provide the synchronous sampling. Again, linear interpolation was applied when the number of samples per revolution was not an integer value. The resulting variance is shown in Fig. 10. It is seen that the values are somewhat higher due to the slightly asynchronous trigger, but the large relative increases in variance are still available to indicate the transition from stable to unstable cutting. This particular implementation requires only the unidirectional microphone, a single channel of data acquisition, simple data processing to calculate the variance based on the nominal spindle speed, and a real-time display to provide condition-based monitoring of the milling stability.

4. Conclusions

A chatter detection technique for condition-based monitoring of milling process stability, based on the statistical variance in the once-per-revolution milling audio signal, is described. This method uses the synchronous and asynchronous nature of stable and unstable cuts, respectively, to identify regenerative chatter. Specifically, it relies on the fact that stable cuts generate content synchronous with spindle rotation and, therefore, the once-per-revolution milling signal is characterized by a tightly spaced cluster of values with a corresponding low variance. Unstable cuts caused by regenerative chatter, however, demonstrate asynchronous motion and give a more distributed set of once-per-revolution values with a subsequently larger variance. A comparison of

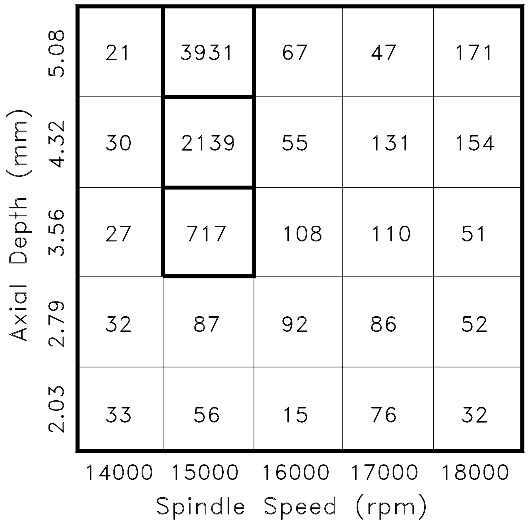

Fig. 10. Variance values in mV^2 for cutting tests using synthetic nominal spindle speed once-per-revolution trigger.

variance values for a number of stable and unstable cuts was completed for various strategies in obtaining the once-per-revolution trigger, which included: (1) obtaining the once-per-revolution signal using a locally derived trigger; (2) generating a synthetic once-per-revolution sampling trigger using the actual spindle speed; and (3) producing the once-per-revolution signal from the nominal (commanded) spindle speed. In all cases, the calculated variance values detected the transition from stable to unstable cutting.

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