REMOTE BAYESIAN UPDATING FOR MILLING STABILITY

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INTRODUCTION

Machining stability is an important limitation in high-speed machining. The physical mechanism for unstable machining, or chatter, is the regeneration of surface waviness during material removal [1]. Stable operating parameters in milling may be selected using the stability boundary, which separates stable spindle speed-axial depth of cut combinations from unstable (or chatter) combinations [1]. While analytical models exist to predict machining stability, their cost-efficient implementation can be hampered by the need for information on the tool point frequency response function (FRF) and the cutting force coefficients. Without knowledge of the tool point FRF and the cutting force coefficients for the tool-material combination, machining parameters are typically selected using tool supplier and handbook recommendations, or previous experience. If unstable behavior (chatter) is observed, the parameters are often adjusted by trial and error until stable behavior is obtained. Typically, this means reducing the spindle speed and axial depth of the cut. In this work, remote identification of optimal stable milling parameters with Bayesian learning using test results is presented. The test cuts were monitored with a wireless sensory tool holder instrumented with an accelerometer. The test results were analyzed for stability remotely, used to learn the stability boundary, and recommend parameters for the next test using a Bayesian learning approach. The iterative process was repeated until convergence to a stable optimal process parameter set was achieved. The described approach can be automated to enable optimizing machining processes in production environments through data sharing with a central location where the analysis is completed.

REMOTE BAYESIAN UPDATING FOR MILLING STABILITY

The procedure for remote Bayesian updating for milling stability is as follows. Milling tests were performed on a milling machine at the TU Wien, Vienna, Austria. The milling tests were monitored using a wireless sensory tool holder instrumented with an accelerometer [2, 3]. The accelerometer data was shared through the cloud with Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA, and the University of Tennessee, Knoxville, Tennessee, USA. The recorded data from a milling test cut was used to classify the cut as stable or unstable based on the frequency content [1]. The test cut result was given as input to a Bayesian learning algorithm for milling stability. The algorithm updated the probability of stability as a function of axial depth of cut and spindle speed based on the test results [4]. The probability of stability was subsequently used to recommend the axial depth and spindle speed for the next test cut based on a maximum expected improvement in the material removal rate criterion. The optimal test parameters were then communicated back to TU Wien in real-time for subsequent testing. The iterative process between two transatlantic locations was repeated until convergence to a stable optimal process parameter set was achieved.

TEST SETUP AND MONITORING

The milling tests were performed on a DMG MORI DMU 75 monoBLOCK milling machine at TU Wien, Vienna, Austria. The workpiece material was Aluminum 6060-T6. Figure 1 shows the test setup. The tool was a 10 mm diameter four flute solid carbide end mill. The axial depth of cut and spindle speed range for the testing was 0 mm – 8 mm and 5000 rpm – 9000 rpm. The radial depth of cut was

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2 mm and feed per tooth was 0.1 mm/tooth. The cuts were down-milling. The workpiece was saved after each test cut to enable inspection of the machined surface. To ensure tight and repeatable clamping of the workpiece, specific vice jaws were used.

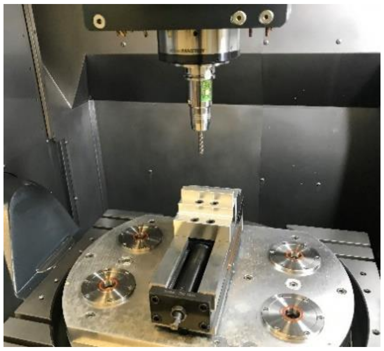

Figure 1. Setup for the cutting tests.

The test cuts were monitored with a wireless sensory tool holder instrumented with an accelerometer [2, 3]. The sensory tool holder can be used for process monitoring and process control and is depicted in detail in Figure 2. Without changing the outer contour of the tool holder, a battery, telemetry system, and an accelerometer mounted on a circuit board have been integrated into the holder. The accelerometer measures the radial acceleration of the tool holder vibration and has a range of up to +-100 g. The vibration data is transmitted out of the rotational system to the receiver unit via a wireless digital communication link, based on Bluetooth low energy [3]. The receiver unit forwards the time-stamped data to a processing unit. A laptop can be used for saving the data as a .csv file to the cloud. The sensor and radio transmission system was installed directly into an HSK-A 63 tool holder as shown in Figure 2.

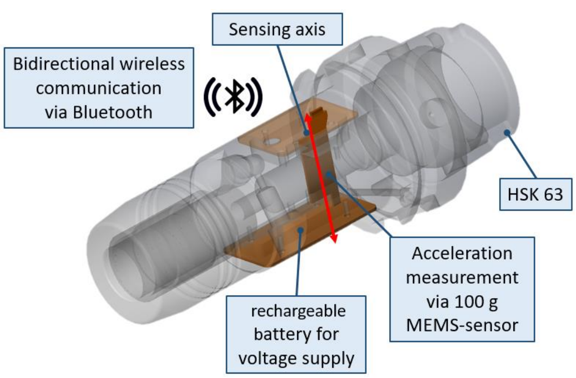

Figure 2. Sensory tool holder [3].

STABILITY CLASSIFICATION

The accelerometer data was shared through the cloud with the analysis framework implemented at the Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA, and the University of Tennessee, Knoxville, Tennessee, USA. The first step of the analysis framework was to classify the test cut as stable or unstable based on the accelerometer data. The stability classification was performed using frequency analysis. For stable cutting conditions, there is frequency content only at the tooth passing frequencies and its harmonics. For unstable test cuts, there is content at chatter frequencies in addition to the tooth passing frequencies. Note that since the accelerometer in the sensory tool holder is not stationary, the frequencies are split by the spindle rotational frequencies [3]. To illustrate, Figure 3 shows the frequency spectrum of the accelerometer data from the sensory tool holder for the test at {9000 rpm, 4 mm} using. The tooth passing frequency is 600 Hz and the spindle rotational frequency is 150 Hz. Due to the nonstationary nature of the accelerometer, the tool passing frequency is split by the spindle rotational frequency at 450 Hz and 750 Hz. To compare, Figure 4 shows the FFT from a sound measurement of the same test cut measured with a microphone. The FFT from the sound signal is at the tooth passing frequency and its harmonics.

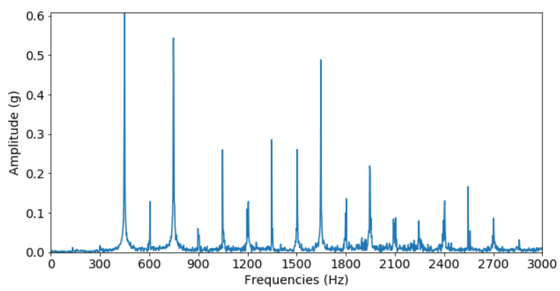

Figure 3. Frequency spectrum for the test at {9000 rpm, 4 mm} using accelerometer data from the sensory tool holder.

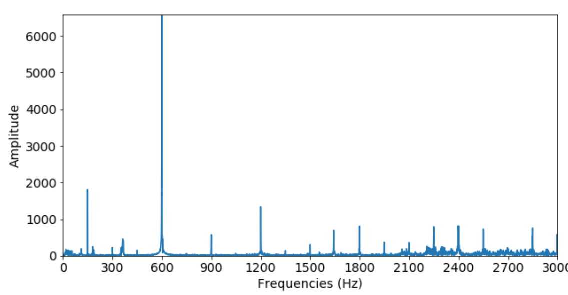

Figure 4. Frequency spectrum for the test at {9000 rpm, 4 mm} using a microphone.

BAYESIAN LEARNING AND TEST PARAMETER SELECTION

The second step of the analysis framework is the Bayesian learning and the test parameter selection algorithms. The Bayesian learning approach updates the probability of stability using test results. Before any tests are performed, a probability of stability map is generated in the spindle speed - axial depth of cut range. This is done by discretizing the spindle speed and axial depth range into grid points and assigning a probability of stability to each point. If the information on the frequency response function is not available, the probability of stability is decided from the knowledge that it is more likely to observe an unstable result at higher axial depths of cut. In this case, the probability of stability is taken to decrease linearly from one at the minimum axial depth of cut to 0.01 at the maximum axial depth of cut. After an experimental result is made available, the probability of stability at each grid point is updated using Bayes' rule as shown in Eq. 1 [4]:

$$p(s_g|r_t) = \frac{p(r_t|s_g)p(s_g)}{p(r_t)} \quad (1)$$

In Eq. 1, *g* is an arbitrary grid point in the spindle speed and axial depth domain and *t* is the test grid point. The test result at *t*, denoted by *r*, can either be stable or unstable. $p(s_g)$ is the prior probability of stability at grid point *g*, $p(r_t | s_g)$ is the likelihood probability of the result *r* at grid point *t* given grid point *g* is stable, $p(r_t)$ is the probability of the test result at grid point t, and $p(s_g | r_t)$ is the posterior probability of stability at grid point *g* given test result *r*, at grid point *t.* The Bayes' learning algorithm considers the physics of the stability boundary for updating the probability of stability. For brevity, the mathematical details of the Bayesian learning algorithm are not included in the paper; the reader is referred to [4] for details. After a test is completed, the result is used to update the probability of stability using Eq. 1. The posterior probability of stability becomes the prior for the next update and so on.

Using the probability of stability, the optimal test parameter is decided based on an expected improvement in material removal rate, MRR, criterion [4]. The expected improvement in MRR at a grid point is given by Eq. 2.

$$E[I(MRR)]_g = p(s_g) \times \frac{(MRR_g - MRR_{prior})}{MRR_{prior}} \quad (2)$$

In Eq. 2, the optimal MRR before a test is completed, denoted as MRR_{prior}, is determined as the optimal material removal rate among parameters that are stable with certainty. The expected improvement in the MRR criterion balances the trade-off between the prior probability of stability and the improvement in MRR if the parameter is stable. To illustrate the Bayes' learning procedure, Figure 5 shows the prior probability of stability. Recall that the axial depth of cut and spindle speed range for the testing was 0 mm – 8 mm and 5000 rpm – 9000 rpm. For the prior probability of stability, it is assumed that the information of the tool frequency response function is not known. The probability of stability decreases linearly from one at 0.01 mm to 0.01 at 8 mm. Note that classical stability analytical models consider stationary dynamics of the tool point FRF in a fixed coordinate frame. The structural dynamics of the instrumented tool holder change as the spindle rotates. It is shown that the stability diagram for a rotating asymmetric dynamic system changes [5]. This further presents the motivation for using an uninformed prior shown in Fig. 5 for the instrumented tool holder with asymmetric rotating dynamics.

The optimal parameter before any test is {9000 rpm, 0.01 mm}. The spindle speed and the axial depth of cut range are discretized in intervals of 10 rpm and 0.01 mm, respectively. The expected improvement in percentage material removal rate at each grid point is calculated using Eq. 2. Figure 6 shows the results. The optimal parameters for the first test are {9000 rpm, 4 mm}; this is shown as a yellow half-circle in Figure 6.

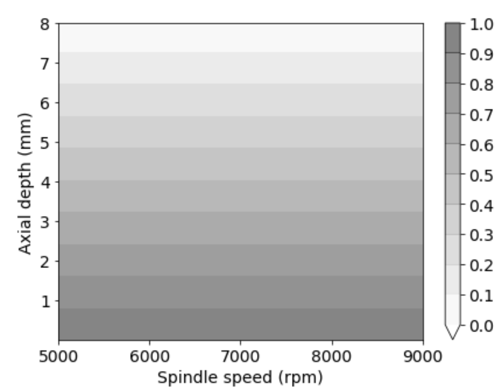

Figure 5. Prior probability of stability.

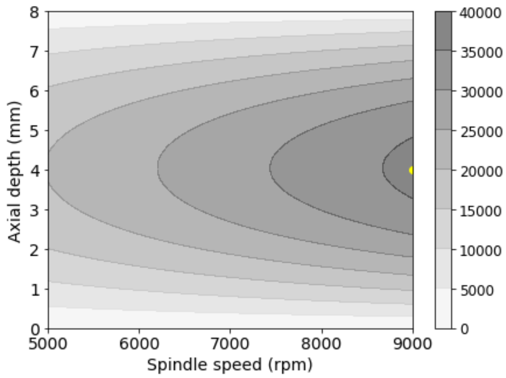

Figure 6. Expected improvement in percentage material removal rate for the first test.

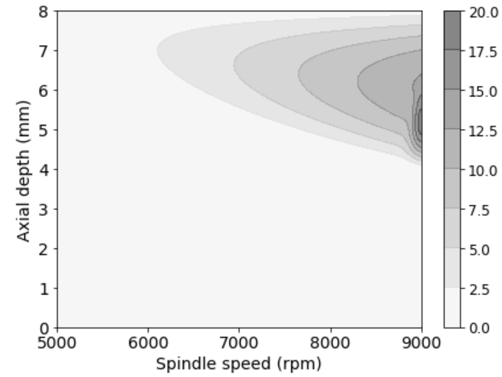

Figure 8. Expected improvement in percentage material removal rate for the second test.

RESULTS

As noted, the optimal test parameters are communicated to the TU Wien, Vienna, Austria. The test parameters were manually entered on the CNC machine and the test was completed. Future work will focus on automating the procedure by communication with the machine controller. The first test at {9000 rpm, 4 mm} was stable (see Figure 3). Figure 7 shows the updated probability of stability using the first test result and Figure 8 shows the expected percentage improvement in MRR for the second test. The optimal parameters for the second test were {9000 rpm, 5.2 mm}. The iterative testing procedure was repeated till the expected improvement in percentage MRR was less than 1%. Figure 9 shows the final results. The optimal parameters were {8700 rpm, 6.7 mm} after 11 tests. The maximum expected improvement in MRR after the 11^{th} test is 0.2%, indicating convergence to the optimal parameters.

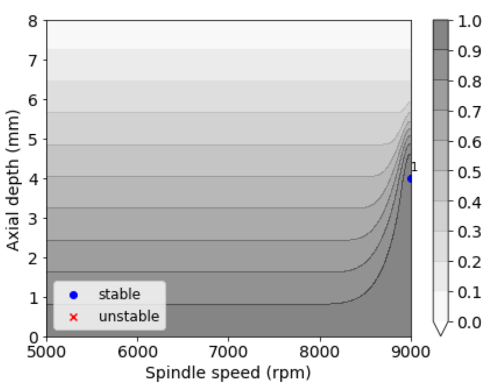

Figure 7. Updated probability of stability after a stable result at {9000 rpm, 4 mm}.

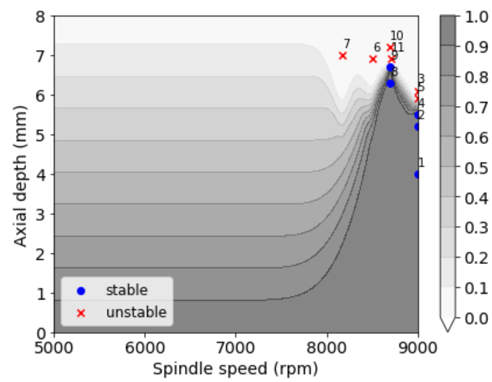

Figure 9. Updated probability of stability after 11 tests; the optimal stable parameters were {8700, 6.7 mm}.

CONCLUSIONS

This paper demonstrated a remote Bayesian learning approach for optimal stable parameter selection in milling. The test cuts were completed at the TU Wien, Vienna, Austria, and monitored with a sensory tool holder instrumented with an accelerometer. The data was shared through the cloud with Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA, and the University of Tennessee, Knoxville, Tennessee, USA. The accelerometer data was used to classify the test cut as stable and unstable. The test result was used to update the probability of stability using a Bayesian learning method and select optimal test parameters, which were communicated back to the TU Wien for subsequent testing. The iterative process between two transatlantic locations was repeated and converged within 11 test cuts, achieving an optimal process parameter set.

The described approach can be automated to enable optimizing machining processes in production environments through data sharing with a central location where the analysis is completed. The sensory tool holder enables continuous monitoring of the milling process. The combination of sensory tool holder and Bayesian stability map updating enables optimizing milling operations across different machines and tools. Future work will focus on monitoring production parts with the sensory tool holder and enabling a self-optimizing milling operation, where process parameters are updated in each successive run to converge to the optimal stable parameters.

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