# Rapid online chatter detection in milling using aliased signals

Harsh Singh Rajput and Mohit Law*

Machine Tool Dynamics Laboratory,
Department of Mechanical Engineering,
Indian Institute of Technology Kanpur,
Kanpur, 208016, Uttar Pradesh, India
Email: rajputmithlesh2@gmail.com
Email: mlaw@iitk.ac.in
*Corresponding author

**Abstract:** This paper proposes a new real-time capable chatter detection method using aliased signals. Since vibration spectra of stable cuts are dominated by harmonics of spindle frequencies, and since aliased signals with known frequency content fold in deterministic ways, we show that we can deduce which of the peaks in the frequency spectra of the folded signals is a harmonic or not of the spindle frequency. We illustrate chatter detection with slot milling Aluminium by sampling at rates as low as 256 Hz. The method takes ~0.13 ms to execute making it useful for condition monitoring and detection of chatter.

**Keywords:** chatter; online; aliasing; milling; real-time; Nyquist.

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**Biographical notes:** Harsh Singh Rajput was a Dual degree (BTech – MTech) student in the Department of Mechanical Engineering at the Indian Institute of Technology Kanpur, India. His research interest lies in the field of tool vibrations, exploring computer vision as an alternative to contact type sensors for acquiring vibrations data. He has also embarked research in the intersection of machine learning and modal analysis, which is a step towards establishing improved condition monitoring of machine tool systems.

Mohit Law is an Associate Professor at the Department of Mechanical Engineering at the Indian Institute of Technology Kanpur, India. He received his PhD from the University of British Columbia, Canada. His research interests centre on understanding how and why machine tools vibrate, measuring those vibrations, and on how best to mitigate them.

## 1 Introduction

In milling, chatter of the regenerative kind occurs due to the phase difference between vibrations imprinted on the machined surface by the rotating, vibrating tool. The phase difference modulates forces that modulate the response. Under certain combinations of excitations, these modulations grow to result in large amplitude chatter vibrations. Since chatter can damage parts of the machine tool system and the machined workpiece (Yang et al., 2018), avoiding it is important (Da Silva et al., 2013; Mancisidor et al., 2019). Chatter avoidance is usually based on model-predictions that guide which combination of cutting parameters will result in stable cutting, and on online detection and suppression. Though the prediction route is important, due to vagaries and uncertainties in the system, online detection and suppression is usually more effective (Munoa et al., 2016). And, for effective suppression, online detection is necessary. This forms the focus of this paper.

Chatter detection is usually based on monitoring the cutting process with sensors. Detection could be done using time-domain approaches, frequency domain approaches, and even by using data-driven approaches. Reviews of these methods has been presented in Zhu and Liu (2020), Wang et al. (2022) and Devia et al. (2023). Regardless of approach, because chatter vibration frequencies are near the natural frequencies, which in machine tool systems can range up to a few kHz, detection requires the process to be monitored at rates of up to tens of kHz. Acquiring and processing such reams of data to continuously monitor and detect chatter is computationally heavy and hence non-trivial. Rapid and accurate online detection of chatter has indeed been one of the main obstacles in making machine tools smart and autonomous. To address this need for a fast and lightweight solution for condition monitoring and online chatter detection, this paper presents a new method.

Prior related research on rapid online chatter detection methods has mostly relied on using the short time Fourier transform method (Zhu and Liu, 2020; Wang et al., 2022; Devia et al., 2023). By using small windows of data, processing time for computing the vibration Fourier spectra is saved. However, since these methods classify the cut as being unstable when the vibration spectra have frequency components other than harmonics of the spindle frequency, and since use of small windows may result in a loss of frequency resolution, such methods often are not very accurate. Other recent frequency domain methods were based on a moving variance moving Fourier transform power ratio method and on using the principal component analysis (Bahtiyar and Sencer, 2022). Though the principal component method was reported to be robust, it was computationally heavy. Whereas, though power ratio method was reported to be near real-time capable, computational times for detection were not reported. Yet other time domain chatter detection methods that are reported to be near real-time and that are based on vibrational energy (Caliskan et al., 2018) and entropy (Hauptfleischová et al., 2022) require tuning of several parameters for working effectively.

Almost all the online chatter detection methods, including those discussed above, work with data sampled at tens of kHz. However, as articulated already, continuously acquiring, and processing such large data is the main bottleneck to effective online detection. As an alternative to sampling at tens of kHz, this paper proposes a new lightweight solution that works with aliased signals, i.e., with signals that are typically sampled at rates of hundreds of Hz and that do not necessarily respect the Nyquist rate.

The method works by exploiting the folding property of temporally aliased signals. In using folding properties of signals, we leverage learnings from our prior work on recovery of modal parameters from potentially temporally aliased signals (Law et al., 2022; Lambora et al., 2022). In that work, since no a priori information of the modal order of the system was assumed, we used notions of set theory to find true modes from observed ones from signals sampled at two fractionally uncorrelated sampling frequencies. However, since in the present case we know that a stable cut is dominated by frequency content corresponding to the spindle frequency and/or its harmonics, and since aliased signals with known frequency content fold in deterministic ways, we show that it is possible to deduce which of the peaks in the frequency spectra of the folded signals is a harmonic or not of the spindle frequency. Using this method, we can easily detect chatter. And, since the method works with less data, it is an order of magnitude more computationally efficient than the standard frequency domain approach and is hence, as we will show, is more suitable for real-time implementation.

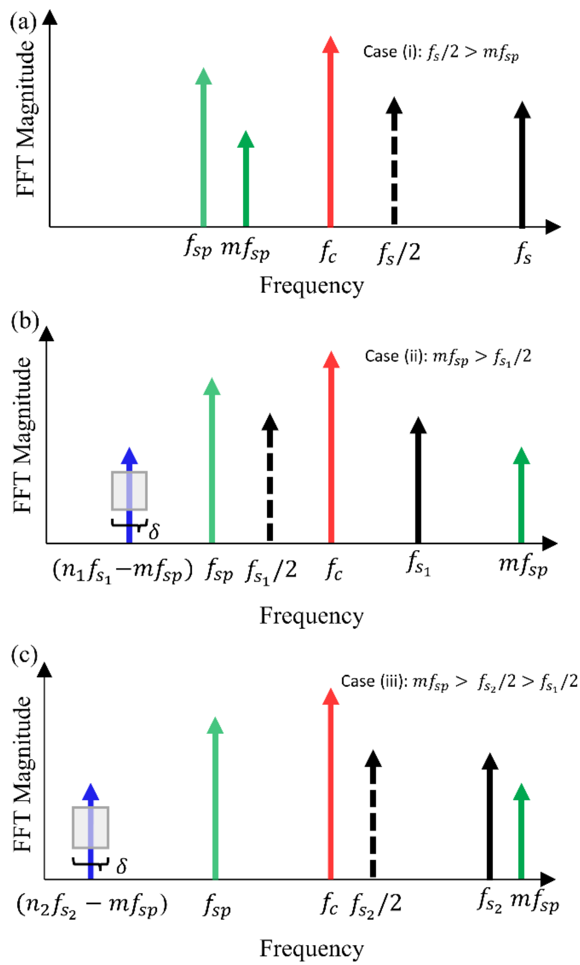
The remainder of the paper is structured as follows. We first outline the workings of the proposed method in Section 2. The experimental setup to monitor and detect chatter in slot milling of Aluminium is discussed in the third section. To detect chatter, we use the preferred (Zhu and Liu, 2020; Wang et al., 2022; Devia et al., 2023) and simple frequency domain approach in which we Fourier transform the aliased signal and classify chatter when the spectrum is dominated by frequency content other than folded harmonics of the spindle frequencies. Results and real-time capability of the method are discussed in the fourth main section. This is followed by final conclusions.

### *1.1 Chatter detection using aliased signals*

Consider that the cutting process is being monitored with a sensor for which data is acquired uniformly at a sampling frequency of $f_s$. Consider also that this sampling frequency is sufficient to respect the Nyquist rate, i.e., the signal is not aliased. Consider also that the data is being acquired at the same rate for all combinations of cutting conditions. Consider also that the cut is stable. For such a case, the spectra in the Fourier transform will be dominated by the spindle frequency, $f_{sp}$ and/or its harmonics $mf_{sp}$, wherein $m$ is the harmonic number. Now, if the cut was to be unstable, say for example that if the speed was kept the same and the depth of cut was increased such that it became a case of chatter, the spectra would instead be dominated by the chatter frequency $f_c$. Classifying the cut as stable/chatter would hence be straightforward. This case in which sampled data satisfies the Nyquist rate is shown schematically in Figure 1(a) as Case (i).

Now, consider a second case in which the same process with the same cutting conditions and spindle speed is being monitored with a sampling frequency $f_{s_1}$ that is less than the rate required to properly resolve the harmonics of the spindle frequency, i.e., $mf_{sp} > f_{s_1}/2$. In such a case, even if the fundamental spindle frequency is properly resolved, the $m$th harmonic of the spindle frequency will fold to lie within the $\{0, f_{s_1}/2\}$ range. And, depending on the difference between $f_{s_1}/2$ and $mf_{sp}$, there can be many different folds of $mf_{sp}$ within the $\{0, f_{s_1}/2\}$ range. We designate this fold number to be $n$. For this case, the fold number is arbitrarily designated as $n_1$. This folding of the frequency spectra from an aliased signal is shown schematically in Figure 1(b) for this case that is designated as Case (ii).

**Figure 1** (a) When acquisition follows the nyquist criteria, i.e., $\frac{f_s}{2} > mf_{sp}$, wherein $f_s$ is the sampling frequency, $f_{sp}$ is the spindle frequency, and $m$ is the harmonic number, there is no folding and observed frequencies are true. (b) Wahen frequencies of interest, i.e., the harmonics of the spindle frequencies are greater than half of sampling rate, i.e., when $mf_{sp} > f_{s_1}/2$, wherein $f_{s_1}$ is less than $f_s$ shown in Figure 1(a), folding of signal occurs and observed frequencies are a function of the sampling rate and fold $n$ and of the harmonic $m$ of the spindle frequency. (c) For a different sub-nyquist sampling rate that that in Figure 1(b), i.e., with $mf_{sp} > f_{s_2}/2 > f_{s_1}/2$ the observed frequency and the value of '$n$' may change accordingly (see online version for colours)




Consider now a third case in which we monitor the same process as in cases (i) and (ii), only now we sample the signal with a different and higher sampling frequency than the second case, i.e., $f_{s_2} > f_{s_1}$ but the signal remains aliased such that $mf_{sp} > f_{s_2}/2 > f_{s_1}/2$. In this case the *m*th harmonic of the spindle frequency will fold to lie somewhere within the $\{0, f_{s_2}/2\}$ range. And, since $f_{s_2} > f_{s_1}$, it may fold with a different fold number. The fold number in this case is arbitrarily designated as $n_2$. Folding is shown schematically in Figure 1(c) for this case that is designated as Case (iii).

In the three cases discussed above, we always assume that an unstable cut's frequency spectra will be dominated by the chatter frequency $f_c$. However, sometimes a cut can be at the margin of (in)stability. In such a case, it is likely that the frequency spectra can have a peak corresponding to a chatter frequency that competes in amplitudes to peaks of the harmonics of spindle frequencies or folds of such harmonics. Classifying chatter in such cases could be done with thresholds on amplitudes of competing peaks in the spectra (Zhu and Liu, 2020; Wang et al., 2022; Devia et al., 2023). Though such cases are ignored in the present work, they can easily be incorporated in the proposed approach, and that can form part of future follow-on research.

For cutting that is stable, it is possible that higher harmonics may dominate the frequency spectrum, i.e., *m* can be any whole number. This can happen with and without aliased signals. However, for the aliased case, for any *m*, it is possible that the fold number, $n$ can also be any whole number. The fold number and the harmonics of interest will also depend on the sampling frequency. Hence, to correctly classify the cut as stable, we create and search within an array $S$ defined as:

$$S = \left\{ \begin{array}{c} nf_s + mf_{sp} \\ nf_s - mf_{sp} \end{array} \right\}; m, n \in W\, S \geq 0 \tag{1}$$

wherein $f_s$ can be any sampling frequency that respects the Nyquist rate or not. If the observed frequency in the Fourier spectra of a signal sampled at any arbitrary rate lies in the array $S$, then that signal is classified as a stable cut. Otherwise, the signal is classified as unstable or chatter. It is important to note here that we force elements within $S$ to be non-negative, and that the array also covers tooth passing frequencies which are multiples of spindle frequencies. Furthermore, to cover all possibilities of $S \geq 0$, $n$ should be at least $m$, i.e., $n \geq m$. We further introduce a tolerance of $\delta$ in our search of the folded frequencies. This tolerance is shown schematically in Figure 1. The tolerance covers any potential errors that may result from loss of frequency resolutions due to sampling at very low rates. It is further important to note that when the signal is properly resolved, $n = 0$.

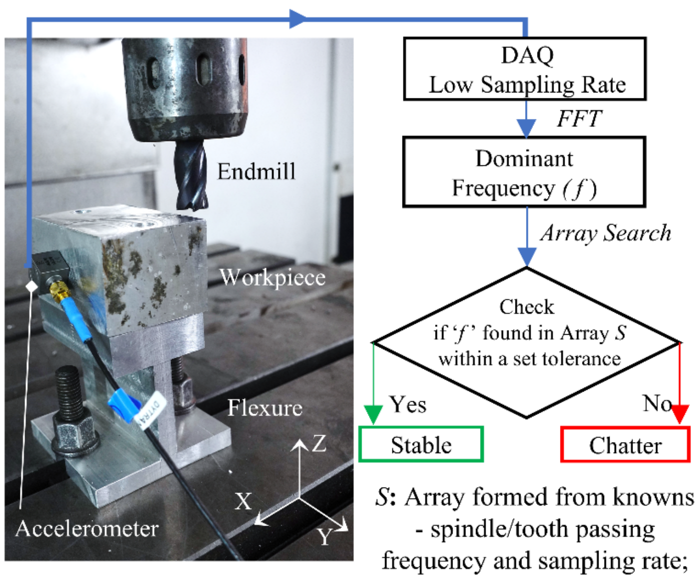
Having outlined the method to detect chatter from aliased signals, we next discuss the experimental setup with which we illustrate the workings of the method.

## 2 Experimental setup

We illustrate the method by slot milling Aluminium. The experimental setup to cut and monitor the process in shown in Figure 2. We use an ACER AMSL-make 3-axis vertical CNC milling machine. We mount the workpiece on a flexure that behaves like a single degree of freedom system with its dominant mode along the X-direction being orders of magnitude more flexible than the tool. We use a regular carbide end mill with a diameter of 16 mm and that has four teeth. To monitor the process, we use a triaxial accelerometer (ENDEVCO 44A16-1032) that is stud mounted on the workpiece-flexure system. All signals are acquired using a NI-DAQ system (NI-9234 + NI-9171) and the Data Acquisition Toolbox in MATLAB.

To guide cutting experiments on this setup, we generate analytical stability lobes using the measured dynamics and the identified cutting force coefficients. The dynamics of the workpiece-flexure system were measured with a modal test and are characterised by a single mode with a natural frequency of 266 Hz, a damping ratio of 0.5% and a modal stiffness of $1.2\times10^6$ N/m. Mechanistically identified tangential and radial cutting force coefficients from previous experiments with the same workpiece and tool were identified to be $824\ \text{N/mm}^2$ and $225\ \text{N/mm}^2$, respectively (Bari et al., 2021). With these parameters, we predicted the stability diagram using the standard zero-order frequency domain approach (Altintas and Budak, 1995). Guided by this diagram we cut to detect if the process is stable or not using the method outlined in Section 2 and in the flowchart in Figure 2. Since we use a NI-9234 data acquisition module for which the minimum sampling rate is 1.652 kHz, all signals were originally acquired at rates of 25.6 kHz and then downsampled in real time to rates of 256 Hz, 341 Hz, and 512 Hz respectively. The feed for all experiments was held constant at 0.05 mm/tooth-rev.

**Figure 2** Experimental setup for slot milling an aluminium workpiece using a carbide end mill along with the flowchart for monitoring and chatter detection using the proposed approach (see online version for colours)



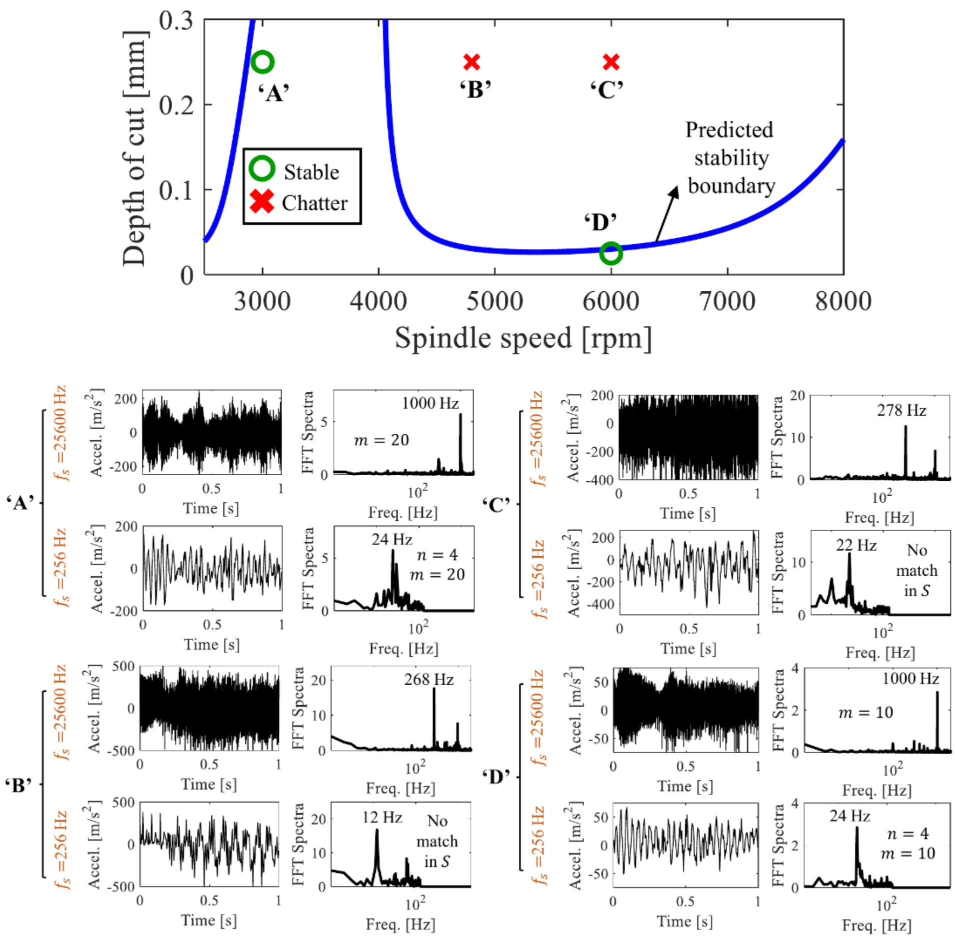

## 3 Results and discussions

We discuss results in this section for detection of chatter with properly sampled and with aliased signals. We first present results guided by the predicted boundary for one aliased rate with a fixed tolerance $\delta$. We then discuss the influence of sampling rates. We subsequently discuss the real-time capability of the method.

## 3.1 Detecting chatter with aliased signals

We conducted four experiments guided by the predicted stability boundary as shown in Figure 3. For all experiments, we also show the measured accelerations and the corresponding Fourier spectra. Since it is difficult to distinguish chatter from transients being excited during tool entry and exit (Bachrathy et al., 2021; Rahimi et al., 2021) we clip all signals to retain only the steady state response, i.e., when the tool is fully engaged with the workpiece. Based on the frequency spectra being dominated by harmonics of spindle speed or not, two of these cuts were classified as stable (points 'A' and 'D') and two as chatter (points 'B' and 'C') – as shown in Figure 3.

**Figure 3** Analytically predicted stability diagram with four experimental cutting points (top): 'A: 3000 rpm, 0.25 mm', 'B: 4800 rpm, 0.25 mm', 'C: 6000 rpm, 0.25 mm', and 'D: 6000 rpm, 0.025 mm'. Bottom: Properly resolved and aliased acceleration signals with their respective Fourier spectra for the four cutting points. For the aliased signals, the corresponding fold number and harmonic numbers are also listed in spectra (see online version for colours)



For the case of the properly sampled signals with the sampling frequency being 25.6 kHz, the frequency spectrum for the stable case is dominated by a peak corresponding to the 20th harmonic ( $m = 20$ ) of the spindle frequency (or the 5th harmonic of the tooth passing frequency) for cutting at point 'A', i.e., at a speed of 3000 rpm. For cutting at the other stable point 'D' at 6000 rpm, the Fourier spectrum is dominated by a peak corresponding to the 10th harmonic ( $m = 10$ ) of the spindle frequency. For the two cases of chatter (points 'B' and 'C' in Figure 3), the Fourier spectra for both cases does not contain any content around the spindle frequency and/or its harmonics. The spectra are instead dominated by peaks higher than the natural frequency of the system – confirming that this is indeed a case of chatter. The acceleration signals for the cases of chatter are also of significantly higher magnitudes than for the stable cases.

For the case of the sampling frequency being 256 Hz, the signals will clearly be aliased even for cutting at the low spindle speeds of 3000 rpm. Since the tooth passing frequency in this case will be 200 Hz ( $4\times f_{sp}$ ), sampling at 256 Hz is not sufficient to respect the Nyquist rate. Likewise, the signal will be aliased for cutting at higher speeds too. However, using the folding properties of the aliased signal, we construct the array $S$ . To construct $S$ , we choose $m = n = 50$ . Limiting the array to lower harmonics is also possible if instead of spindle frequencies, the array was being constructed with tooth passing frequencies.

We then search within this array and find that for cutting at point 'A' that is stable, the array contains an entry at 24 Hz. This peak corresponds to what is observed in the spectra of the aliased signal. The entry within the array corresponding to he observed peak is evaluated as per equation (1), i.e., for the spindle frequency ( $f_{sp}$ ) being 50 Hz and the sampling frequency being ( $f_s$ ) being 256 Hz, and with $n = 4$ and $m = 20$ . Likewise for cutting at point 'D', there is a peak in the spectra of the aliased signal at 24 Hz. This corresponds to an equivalent entry in the array which is evaluated for $f_{sp}$ being 100 Hz, and $f_s$ remaining 256 Hz, with $n = 4$ and $m = 10$ .

For the case of cutting at points 'B' and 'C', the peaks observed in the aliased spectra do not correspond to any element within the array $S$ constructed for those speeds and the same sampling frequency. As such, as per our criterion, these cases are classified as chatter. To construct $S$ , the tolerance, $\delta$ for the sampling frequency being 256 Hz, was set as 0.2 Hz. Since the differences in the peaks of the aliased signals for cutting at point 'C' and point 'D' is only 2 Hz, a larger tolerance might have made it difficult to correctly classify if a cut was stable or not.

## 3.2 Influence of sampling frequency on results

Results above were limited to properly sampled signals and one aliased rate. This section discusses the influence of other low rates of sampling on the chatter detection ability. The three sampling rates compared herein are 256 Hz, 341 Hz and 512 Hz, respectively. And, instead of showing the spectra of the aliased signals, we tabulate the observed frequency in the spectra of the differently sampled signals and list the corresponding matching frequencies within the different arrays $S$ along with the corresponding fold number and harmonic numbers. These results are listed in Table. 1. Results in Table 1 are limited to only those cuts that are stable, i.e., points 'A' and 'D' as marked in Figure 3. Since the tooth passing frequencies for cutting at 3000 rpm and 6000 rpm are 200 Hz and 400 Hz, respectively, all three signals are aliased.

As is evident from comparisons in Table 1, for the three different sampling rates, at least one element within the array *S* match with observed peak in aliased spectra. The only influence of sampling rate is that the fold number changes with changing sampling frequencies.

**Table 1** Matching frequencies in array *S* for observed frequency along with the corresponding fold number and harmonic numbers

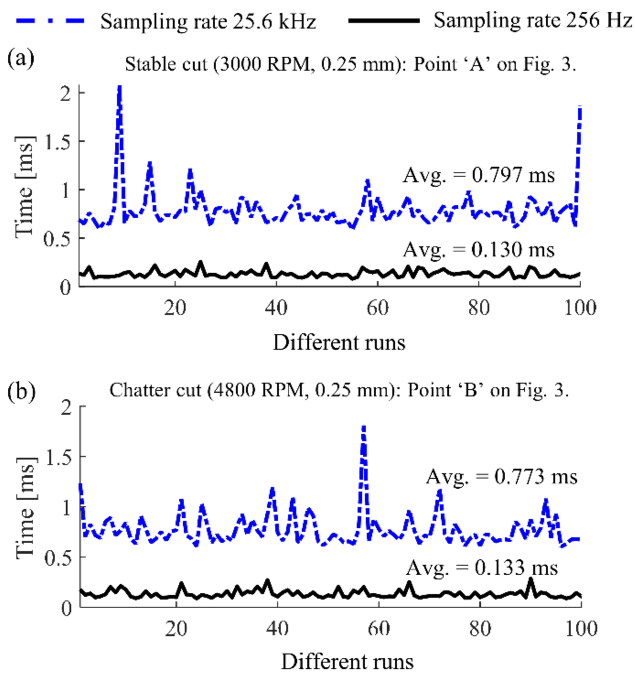
| *Cutting at (speed, depth of cut);* $f_{sp}$ | *Peak frequency observed in the aliased spectra* | *Element within S that matches observed peak in aliased spectra* ($nf_s - mf_{sp}$) $f_s$ *256 Hz* | $f_s$ *341 Hz* | $f_s$ *215 Hz* |
|---|---|---|---|---|
| Point 'A' (3000 rpm, 0.25 mm); $f_{sp} = 50$ Hz | 24 Hz | 24 Hz = **4**(256)-**20**(50) $n = 4$, $m = 20$ | 24 Hz = **3**(341)-**20**(50) $n = 3$, $m = 20$ | 24 Hz = **2**(512)-**20**(50) $n = 2$, $m = 20$ |
| Point 'D' (6000 rpm, 0.025 mm); $f_{sp} = 100$ Hz | 24 Hz | 24 Hz = **4**(256)-**10**(100) $n = 4$; $m = 10$ | 24 Hz = **3**(341)-**10**(100) $n = 3$; $m = 10$ | 24 Hz = **2**(512)-**10**(100); $n = 2$; $m = 10$ |

## 3.3 Computational times to detect chatter

Since the main motivation of this research was to propose a rapid and lightweight chatter detection method, this section discusses the computation time required to acquire at low and possibly aliased rates, construct arrays, and search for elements within them that correspond to a fold of the harmonics of the spindle frequency as observed in the Fourier spectra of the temporally aliased signal. We compare this time with the time that the standard technique of acquiring at proper Nyquist-respecting rates and then checking spectrums for harmonics of spindle and tooth passing frequencies to classify the cut as stable or not.

For the aliased cases considered, the time taken to classify the cut as stable or not depends on the size of the array and the searching algorithm used. The size of the array, for all cases under consideration were with *n* and *m* being 50. And to find matches, we used a simple linear search algorithm. For the representative case of sampling at 256 Hz which results in an aliased signal, we find that the average time taken for classifying the cut as stable or not is 0.13 ms. This time is significantly lower than the time taken for detection using the standard method with a properly sampled signal at the rate of 25.6 kHz, which is ~0.78 ms. Figure 4 shows the time history of detection for a 100 different runs on the same data for one representative stable and chatter case. As is evident, there are some fluctuations in the time take. The fluctuations are thought to be due to background processes in the CPU. These times were estimated with implementation of the algorithm on a laptop running MATLAB with a i5-8250U processor running at a base speed 1.8 GHz and with 8 GB RAM. What is however evident is that the proposed method is rapid. The major reason for the decrease in computational time taken by the newly proposed method is processing less amount of data. And, though array searching takes time, the proposed method is clearly real-time capable.

**Figure 4** Summary of time taken over different trial runs to classify the cut as stable for properly sampled signal (at 25.6 kHz) with the standard method and for aliased signals (256 Hz) with the proposed method: (a) stable cut at 3000 rpm, 0.25 mm: Point ‘A’ in Figure 3 and (b) chatter cut at 4800 rpm, 0.25 mm: Point ‘B’ in Figure 3 (see online version for colours)




## 4 Conclusions

Detecting chatter is necessary to avoid and/or suppress it. And, doing so in real-time is imperative such as to avoid damage that chatter can cause to the machine tool system. To address the need for a real-time online chatter detection system, this paper proposed a new method that used aliased signals. Since vibration spectra of stable cuts are dominated by harmonics of spindle frequencies, and since aliased signals with known frequency content fold in deterministic ways, we showed that we could deduce which of the peaks in the frequency spectra of the folded signals is a harmonic or not of the spindle frequency. We did so by creating and searching within an array that included several different folds and harmonics. The array changes with changing speed and sampling frequencies. We illustrated chatter detection with slot milling Aluminium by sampling at rates as low as 256 Hz. We showed that the proposed method only takes ~0.13 ms to execute as compared to the 0.78 ms that the standard method sampling at rates of 25.6 kHz takes.

Though we demonstrate the method with measured accelerations, the method could work with other signals as well. For example, the method would work with sound from microphone, and other signals from other non-contact transducers such as laser displacement sensors and eddy current sensors. The method could also be applied to motor current signals. As such, the method is generalised enough to be used with other machining processes. However, it should be noted that since the method works with low sampling rates, it is likely that only fully stable and fully unstable cuts can be classified correctly. For cuts at the transition of the stability boundaries, i.e., for cuts in which chatter is not fully developed, the method is untested.

And though the method needs to be tested further for its robustness and its ability to detect chatter in other machining process, the real-time capability of our method will make it possible to monitor the system with low sampling rates and will also facilitate the use of wireless transmission devices whose use was mainly precluded by the high sampling rates that were required traditionally. Our use of low sampling rates will also save the effort required to acquire, process and store data. Furthermore, since our system is real-time, it will also facilitate easy self-diagnosis to help make machine tools smarter and more autonomous.

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