COPEN-13

13th International Conference on Precision, Micro, Meso and Nano Engineering

A non-uniform low-rate random sampling-based compressed sensing framework to detect chatter in milling

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Abstract: This paper reports on the successful implementation of a low-rate random sampling-based compressed sensing framework to detect chatter in milling. The method works by randomly sampling the sparse vibration signal during acquisition and solving a minimization problem to reconstruct the original signal from as little as 10% of the original data. We illustrate the method with slot milling. To classify chatter from the reconstructed signal, we check for the frequency spectra being dominated by spindle harmonics or not. Since the method is lightweight and takes on average ~9 milliseconds to execute it is suitable for real time condition monitoring.

Keywords: Compressed Sensing, Chatter, Sparse Signals, Milling, Condition monitoring

1. Introduction

Regenerative chatter is characterized by large amplitude vibrations. Since chatter can damage the workpiece and the machine, detecting it is necessary to suppress it. Detection requires monitoring the process. Since 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 a few kHz. Acquiring, storing, and processing such reams of data to continuously monitor and detect chatter is computationally heavy [1 - 3]. In response to the need for a lightweight solution, this paper introduces a non-uniform low-rate random sampling-based compressed sensing (CS) framework to detect chatter.

The central idea in CS is that if the signal is sparse, it can be recovered from far fewer randomly acquired samples than required by the Nyquist rate [4, 5]. Machine tool vibration signals are usually sparse in the frequency domain. Stable cuts are characterized by spindle rotation frequencies, and unstable cuts by chatter frequencies. CS can hence be easily applied to monitor and classify the cutting process.

Proper CS implementation requires that signals be sampled randomly while being acquired. However, since hardware to randomly sample data is mostly in the prototyping stage [6], we demonstrate recovery by randomly sampling data from signals that are acquired at uniform rates. This is like what was done in prior related work [7 - 10]. That work, however, was concerned with using CS for modal parameter estimation from signals recovered from already acquired and stored data. We instead demonstrate the real-time capability of CS to monitor the process. This is the main new technical contribution of this work.

Of the many different time domain approaches, feature extraction approaches, or data-driven methods to detect chatter, we use the preferred [1, 2] and simple frequency domain approach in which we Fourier transform the signal and classify chatter when the spectrum is dominated by frequency content other than harmonics of the spindle frequencies [3]. We illustrate the method with milling of an Aluminium workpiece, setup for which is discussed in Section 2. The CS method is detailed in Section 3. Section 4 discusses results demonstrating the lightweight potential of the method while accounting for how sensitive the method is to randomness, and to the possible degree of compression. Main conclusions follow.

2. Experimental setup to monitor the milling process

We slot mill an Aluminium workpiece mounted on a flexure using a 16 mm diameter four-fluted carbide end mill mounted in 3-axis CNC milling machine – see Fig. 1. We use a single axis accelerometer to monitor vibrations of the workpiece. We use a NI data acquisition device and MATLAB's toolbox to acquire signals uniformly sampled at the rate of 5.12 kHz. This rate follows the Nyquist criterion. We then implement the CS framework in real time.

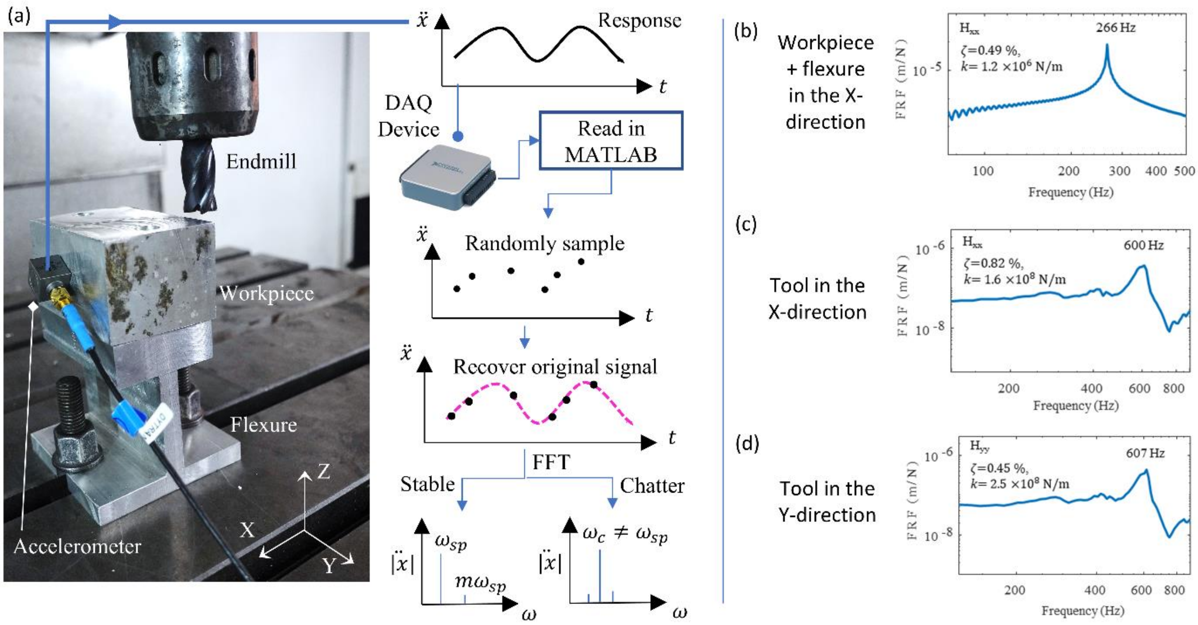

Fig. 1. (a) Experimental setup with a schematic of our implementation of the compressed sensing framework. Slot milling is performed in x direction, along the flexure. (b) – (d) Measured frequency response functions (FRFs) of the workpiece and tool.

To test the algorithm, we cut with a feed of 0.05 mm/tooth-rev with parameters selected using an analytically predicted stability diagram [11] which is generated using measured dynamics and cutting force coefficients. The flexure is designed to be more flexible than the tool – as is evident from the measured FRFs shown in Fig. 1(b) – (d), which also lists the respective modal parameters, which shows that there is just one dominant mode of the flexure and of the tool, and that the tool's modes are two orders of magnitude stiffer. Mechanistically identified tangential and radial cutting coefficients from previous experiments with the same workpiece and tool were [12] 824 $\mathrm{N/mm^2}$ and 225 $\mathrm{N/mm^2}$, respectively.

3. Compressed sensing framework

Consider a $\mathrm{N} \times 1$ time series signal vector $(\boldsymbol{f})$, which is sampled as per the Nyquist rate. A $\mathrm{N} \times \mathrm{N}$ Fourier basis matrix ($\boldsymbol{\psi}$) decomposes the time series signal into a $\mathrm{N} \times 1$ frequency domain loading vector ($\boldsymbol{c}$):

$$\boldsymbol{f}_{\mathrm{N}\times1} = \boldsymbol{\psi}_{\mathrm{N}\times\mathrm{N}} . \boldsymbol{c}_{\mathrm{N}\times1} \tag{1}$$

wherein $\boldsymbol{\psi}$ is obtained from a Fourier transform. If $\boldsymbol{c}$ is sparse in nature, $\boldsymbol{f}$ can be characterized by a few non-zero coefficients in the vector $\boldsymbol{c}$.

Now consider that a few 'M' random values are chosen from the vector $\boldsymbol{f}$, and stored in a measurement vector ($\boldsymbol{b}$). If the indices of the random measurements chosen in $\boldsymbol{b}$ are stored in the form of a $\mathrm{M} \times \mathrm{N}$ dimensional dictionary matrix ($\boldsymbol{\phi}$), then $\boldsymbol{f}$, $\boldsymbol{b}$ and $\boldsymbol{\phi}$ can be related as:

$$\boldsymbol{b}_{\mathrm{M}\times1} = \boldsymbol{\phi}_{\mathrm{M}\times\mathrm{N}} . \boldsymbol{f}_{\mathrm{N}\times1} \tag{2}$$

Eqs. (1) and (2) can be simplified to result in a relation between $\boldsymbol{b}$ and $\boldsymbol{c}$:

$$\boldsymbol{b}_{\mathrm{M}\times1} = [\boldsymbol{A}_{\mathrm{M}\times\mathrm{N}}]\boldsymbol{c}_{\mathrm{N}\times1} \tag{3}$$

wherein $\boldsymbol{A}_{\mathrm{M}\times\mathrm{N}}$= $[\boldsymbol{\phi}_{\mathrm{M}\times\mathrm{N}} . \boldsymbol{\psi}_{\mathrm{N}\times\mathrm{N}}]$.

Our aim is to reconstruct $\boldsymbol{f}$ from a known $\boldsymbol{b}$, $\boldsymbol{\psi}$, and $\boldsymbol{\phi}$. This is equivalent to determining $\boldsymbol{c}$ from Eq. (3). However, since $\mathrm{M} \ll \mathrm{N}$, Eq. (3) is an underdetermined linear system of equations, and there can be infinitely many solutions for $\boldsymbol{c}$. To address this, an additional constraint is introduced to minimize the $\boldsymbol{L}^1$ norm of $\boldsymbol{c}$ [13]:

$$\min\|\boldsymbol{c}\|_{\mathbf{1}} \text{ , subject to } \boldsymbol{b} = \boldsymbol{A}\boldsymbol{c}. \tag{4}$$

Eq. (4) is a convex optimization problem. We solve it using the L1-Magic Optimization Code [14] in MATLAB. Once $\boldsymbol{c}$ is obtained, $\boldsymbol{f}$ can be restored using Eq. (1). For additional details, please see [4, 5].

We test this scheme to characterize the influence of the number and clustering of random samples, and their randomness on reconstruction and detection – as is discussed next.

4. Results

Guided by the predicted stability boundary, we performed five experiments with parameters shown in Fig. 2. Since vibration signals at cut entry and exit are sometimes indistinguishable from chatter [15], signal analysis is restricted to when the tool is fully engaged with the workpiece. Based on the frequency spectra being dominated by harmonics of spindle speed or not, three cuts were classified as stable and two as chatter. Representative uniformly sampled time series data and spectrum of one stable (point 'A') and chatter (point 'B') case is shown in Fig. 2(b). The stable signal has a peak at ~1000 Hz, which is close to the twentieth harmonic of the spindle speed. The chatter signal has a peak at ~284 Hz, which is higher than the natural frequency and is not a harmonic of spindle speed. The spectra in Fig. 2(b) shows only the positive half-spectrum of the FFT of the time response with the X-axis displayed only until 1.5 kHz.

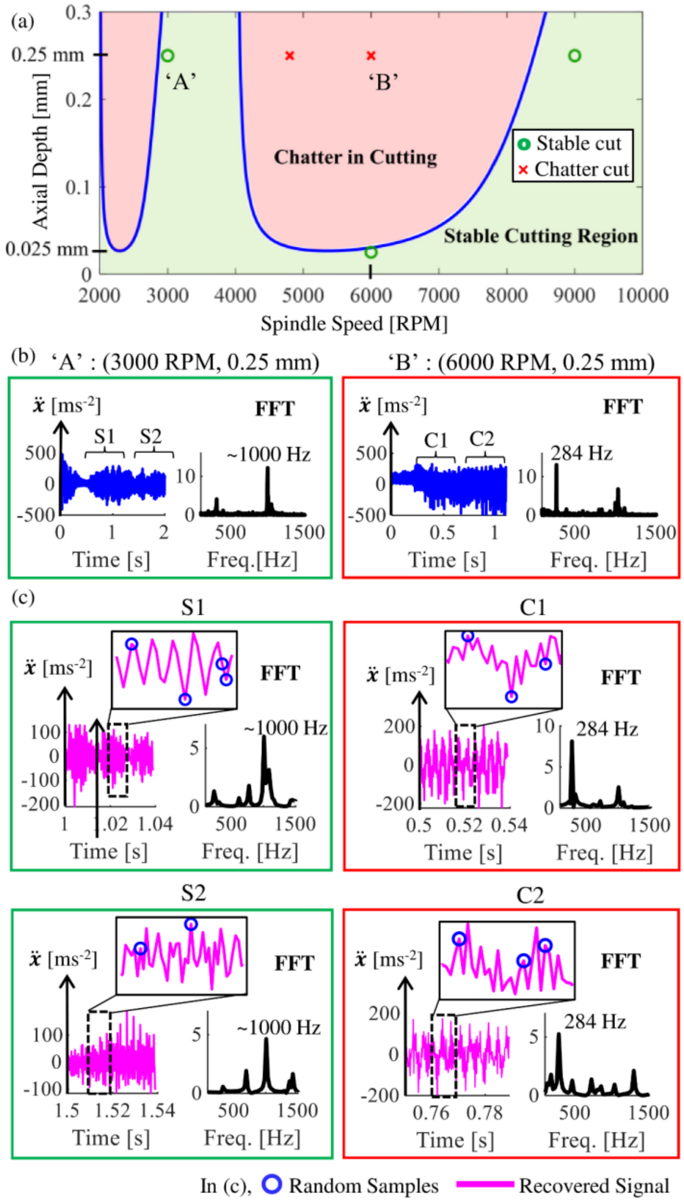

Fig. 2. (a) Cutting guided by predicted stability. (b) Original uniformly sampled response and its spectra for representative cuts at stable and chatter conditions. (c) Signal reconstructed from randomly sampled data in two separate window locations along with its spectra for representative cuts at stable and chatter conditions.

All signals were compressed, and representative results are shown in Fig. 2(c). To demonstrate that reconstruction is independent of clustering, results are shown for two different window locations (S1 and S2 for the stable case, and C1 and C2 for the chatter case). Window size in all cases was taken to be same, i.e., 200 data points. This window size 'N' in Eqs. (1) – (3), chosen arbitrarily. The optimal window size is a potential area for future research. A more deterministic and relevant parameter here is degree of compression, i.e., the ratio of original samples to random samples required for successful reconstruction was found to be 10. Larger window sizes could have resulted in higher compressions, but at the cost of computation effort. CS takes on average ~9 milliseconds to execute and classify the cut as stable or not.

The bulk of this time is consumed in solving the minimization problem. Though the time taken is more than what is required to classify the cut based on a simple FFT of the original uniformly sampled data (for the same window size of 200 data points), which takes on average less than 1 millisecond, given that we acquire, process and store significantly less data with CS, and that we can successfully detect chatter, the method is still advantageous. Times reported are for computations done on a desktop computer with an Intel i7-6700U processor running at a base speed 3.4 GHz and with 16 GB RAM.

To characterize how randomness influences the probability of correct classification and how that varies with the degree of compression, we run a Monte Carlo simulation 100 times to generate 100 different random streams from one window of data. To verify if recovery is proper and classification correct, we check if the dominant frequency in the spectrum of the reconstructed signal is within a 3% tolerance of the known frequency of the properly sampled data. Results for cutting at points 'A' and 'B' marked in Fig. 2 are shown in Fig. 3. As is evident, in general, the degree of compression is lower for higher probabilities of correct classification. However, if a 90% probability is acceptable, when randomness is accounted for, then the degree of compression can be 3.

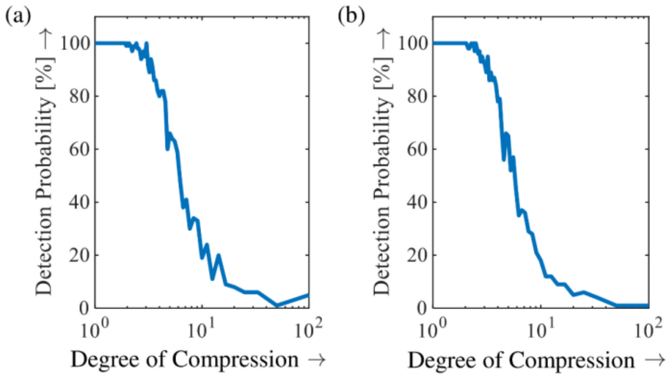

Fig. 3. Variation of detection probability with change degree of compression for (a) Stable cut at 3000 RPM, 0.25 mm and (b) Chatter cut at 6000 RPM, 0.25 mm.

5. Conclusion and outlook

A new lightweight random sampling-based compressed sensing technique was implemented to monitor and detect chatter in milling. Signal reconstruction and classification was shown to be relatively independent of clustering of sampled data. The probability of chatter detection however was found to be a function of the degree of compression. Though random sampling, reconstruction and classification executes in ~9 milliseconds, since this is slower than classification based on a simple FFT of uniformly sampled data, future work could focus on implementing more time-efficient minimization algorithms and on increasing the degree of compression.

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