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USING COARSE-GRAINED ENTROPY RATE TO DETECT CHATTER IN CUTTING

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A new method for chatter detection in turning on a lathe is introduced. It exploits a significant change of cutting dynamics caused by the onset of chatter. The changes are reflected in both dynamical and statistical characteristics. Experimentally, the transition from chatter-free cutting to chatter was achieved by a change of either cutting depth or turning frequency. For the characterization of cutting dynamics the coarse-grained entropy rate is applied. A high value of the entropy rate is typical for chatter-free cutting, while for chatter a low value is typical. For the purpose of chatter detection the normalized value of the entropy rate is used and a characteristic threshold is defined. The value of the threshold is independent of cutting conditions. In addition to chatter detection, the entropy rate is applicable for qualitative physical interpretation of cutting process properties.

1. INTRODUCTION

Tool chatter in cutting is described as a large amplitude vibration of the tool relative to the workpiece. Such vibration leads to poor surface quality and reduced dimensional accuracy of the manufactured workpiece, it reduces tool life and overall productivity rate. Because of its unfavorable effects and frequent occurrence in modern machining, chatter has been studied extensively, both analytically and experimentally [1].

Chatter can be either forced or self-excited [2]. Forced chatter occurs because of cyclic variation of the cutting force, as in milling, or due to intermittent cutting. Self-excited chatter is divided into primary and regenerative chatter. Possible causes for the primary chatter are friction effects between the tool and the cut material, and non-linear dependency of cutting force on cutting speed. Regenerative chatter mainly occurs when the tool cuts an already modulated surface created during previous cuts.

Various methods for the detection of chatter have already been proposed [3–9]. Chatter detection often involves monitoring of the power contained in the power spectra of measured signals. Cutting forces [6], tool accelerations, and audio signals [4] can be used for this purpose. In reference [3] artificial neural networks were applied to detect the sine-wave shape and the frequency of the tool acceleration signal characteristic of chatter. Bispectrum [7] and various measures based on wavelet decomposition were also proposed [5, 8]. A different approach was taken by Li *et al*. [9] who utilized simultaneous measurements of tool accelerations in two different directions and searched for the coherence between them which is established during chatter.

From the point of view of cutting dynamics, the latter method is a step in the direction followed by this article. Detailed time series analysis showed [10] that the onset of chatter represents a transition from high-dimensional to low-dimensional dynamics. The transition is similar to a bifurcation and the corresponding change in the dynamics is significant. It

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is the aim of this article to propose characteristics for chatter detection based on the dynamics of cutting.

2. EXPERIMENTS

2.1. EXPERIMENTAL PROCEDURE

The experimental setup is shown in Figure 1. Two sets of experiments were performed on a lathe. Neither coolants nor lubricants were used. In the first set, cutting depth was chosen as the control parameter, while turning frequency and feed rate were held constant at 640 rpm and 0·04 mm/rev, respectively. The cutting depth was increased slowly and smoothly from 0·1 mm to 1·3 mm, without interruption of the cutting. The increase of cutting depth resulted in transition from chatter-free cutting to chatter. Slow and smooth increase of the cutting depth was needed so as to assure the quasi-stationarity of the cutting conditions. Such an increase was achieved by cutting conical cylindrical workpieces.

In the second set of experiments, the turning frequency, f_c, was selected as the control parameter, while cutting depth and feed rate were held constant at 1 mm and 0·09 mm/rev, respectively. The turning frequency was increased from 350 rpm to 700 rpm in steps of 50 rpm. Chatter was observed only at $f_c = 450$ rpm. However, cutting at $f_c \leqslant 400$ rpm could be described as pre-chatter.

The workpieces were made of steel CS45 (ISO), with a nominal length of 250 mm and a diameter of 50 mm. They were ground in order to avoid variability of cutting depth due to surface roughness.

For the measurements of cutting forces a three-component dynamometer was used, mounted on the slides of the lathe. Time series of feed, F_f, thrust, F_t, and cutting component, F_c, of the main cutting force, $\mathbf{F} = (F_f, F_t, F_c)$, were measured simultaneously. The time series were sampled at a frequency of 5 kHz and each contained 30 000 points. In the first set of experiments, 54 time series of **F** were obtained from the cutting of one conical workpiece. The change of cutting depth during one time series was on the order of its measuring accuracy. In the experiments with variable turning frequency, 16 time series of **F** were recorded, two per each value of turning frequency.

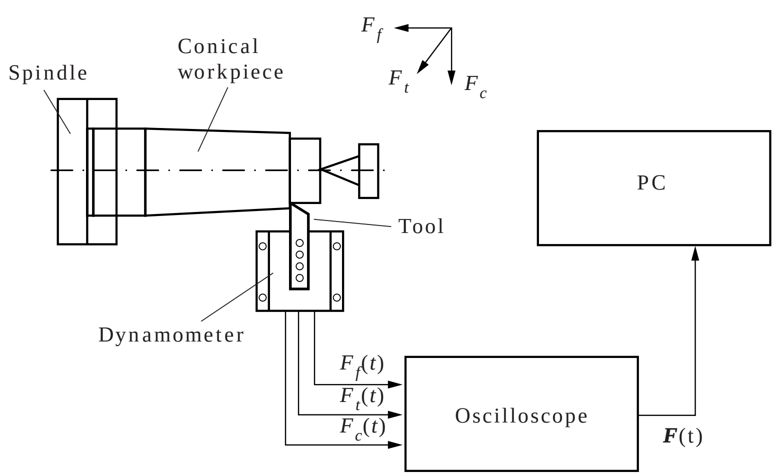

Figure 1. Sketch of the experimental setup.

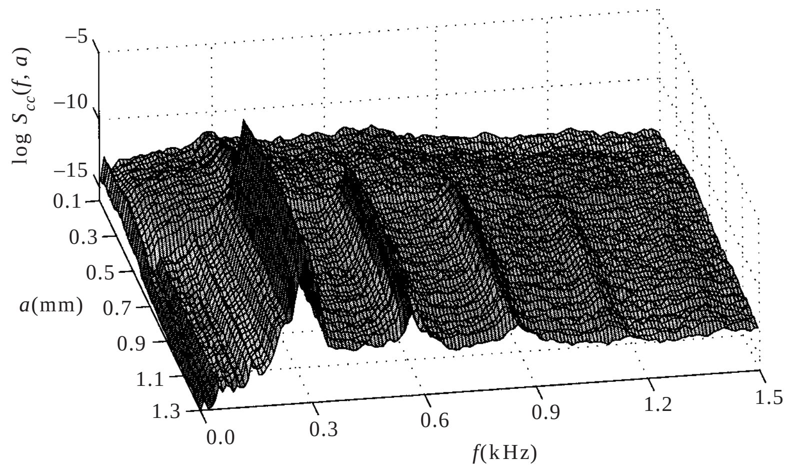

Figure 2. Dependence of the power spectra of the cutting component, F_c, on the cutting depth, a. Two different cutting regimes can be observed.

2.2. TRANSITION FROM CHATTER-FREE CUTTING TO CHATTER

Figure 2 shows the dependence of the power spectra of the cutting component, F_c, on the cutting depth, a. Two different cutting regimes can be observed, separated by the cutting depth $a \approx 0{\cdot}6$ mm. Cutting at lower depths, $a < 0{\cdot}6$ mm, can be described as regular, i.e., absent of chatter, whereas cutting at depths $a > 0{\cdot}6$ mm is accompanied by chatter. The transition to chatter can also be observed in the bifurcation diagram in Figure 3, where the dependence of F_c amplitudes on the cutting depth is shown. Significant increase of the amplitudes of the cutting force indicates the onset of chatter.

According to Figures 2 and 3, the total power, P, contained in the spectrum could be used to detect chatter [Figure 5(a)]. However, a significant increase of P can be caused also by a change in the cutting parameters and not only by the onset of chatter. Similarly, one could monitor the power of certain spectral components or spectral intervals [11], corresponding to the natural frequencies of machine, tool or workpiece. To determine these frequencies, a preliminary analysis should be performed which is not a simple task

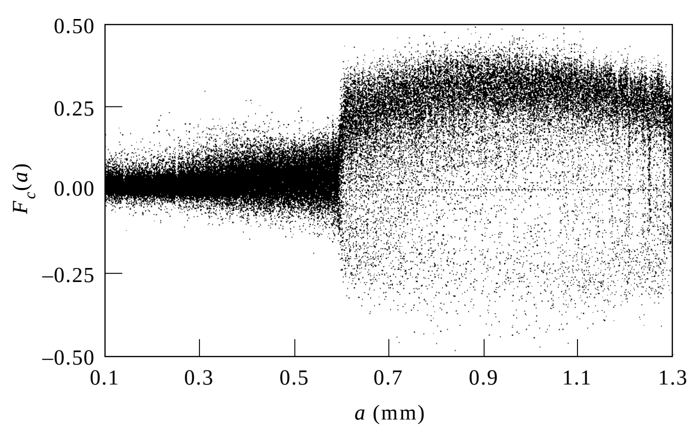

Figure 3. Dependence of the amplitudes of the cutting component, F_c, on the cutting depth, a. Significant increase of the amplitudes indicates the chatter onset.

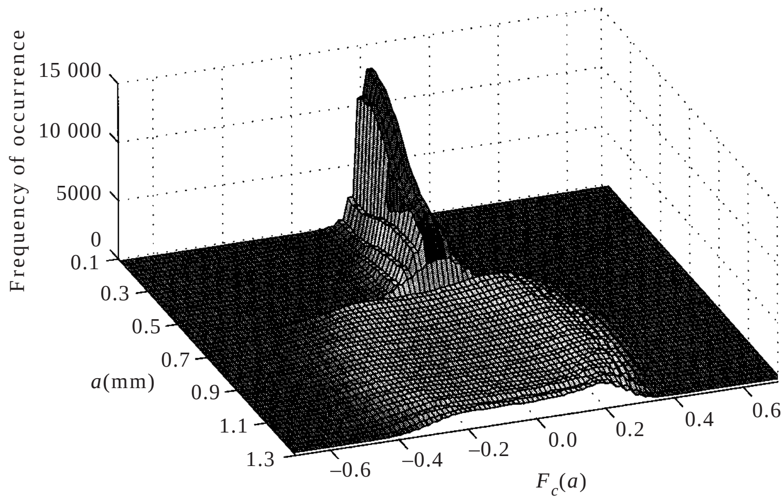

Figure 4. Dependence of the amplitude distribution of the cutting component, F_c, on the cutting depth, a. Chatter changes the distribution from unimodal to bimodal.

[12]. In our case, the highest spectral peak in Figure 2 is located at $f = 275$ Hz which corresponds to a natural frequency of the workpiece at $f \approx 225$ Hz, shifted because of the workpiece-tool coupling.

The dependence of the amplitude distribution of F_c on the cutting depth is shown in Figure 4. It is obvious that the distribution changes as chatter onsets. The distribution is unimodal before the chatter and bimodal during the chatter. Thus, a measure of the difference between the experimental and a Gaussian distribution, such as kurtosis [Figure 5(b)], could be applied to detect chatter. In agreement with some other studies [8], we do not find kurtosis to be a reliable chatter indicator in turning, but it can be useful as a complementary measure.

Analysis of the measured time series by means of non-linear dynamics reveals further differences between the dynamics of chatter-free cutting and the dynamics of cutting accompanied by chatter [10]. Unfortunately, calculation of many non-linear characteristics is noise-sensitive. In most experimental situations the required signal to noise ratios are not easily met thus making the results of the calculations unreliable. Such characteristics

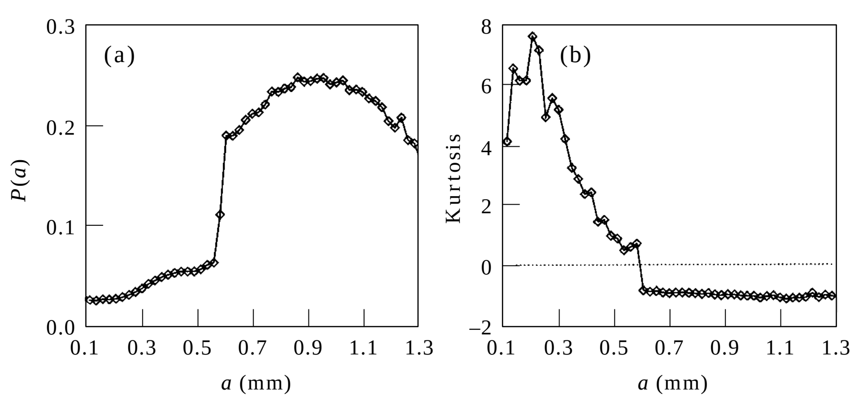

Figure 5. (a) The total power contained in the power spectrum of F_c vs the cutting depth, a. A significant increase of the power indicates the onset of chatter. (b) The kurtosis of the amplitude distribution of F_c vs the cutting depth, a. Negative value of the kurtosis is characteristic for chatter.

are not suitable for on-line application in an industrial environment. Recently, alternative measures for the characterization of the complex time series were proposed [13]. These measures are described in the next section.

3. COARSE-GRAINED ENTROPY RATE

Consider m discrete random variables, $X_1, \ldots, X_m$, with sets of values $\Psi_1, \ldots, \Psi_m$, respectively. Their individual probability distribution functions are denoted by

$$p(x_i) = \Pr\{X_i = x_i\}, \qquad x_i \in \Psi_i, \tag{1}$$

and similarly their joint probability distribution function is

$$p(x_1, \ldots, x_m) = \Pr\{(X_1, \ldots, X_m) = (x_1, \ldots, x_m)\}, \qquad (x_1, \ldots, x_m) \in \Psi_1 \times \cdots \times \Psi_m. \tag{2}$$

The marginal redundancy, $R'(X_1, \ldots, X_{m-1}; X_m)$, defined as [13, 14]

$$R'(X_1, \ldots, X_{m-1}; X_m) = \sum_{x_1 \in \Psi_1} \cdots \sum_{x_m \in \Psi_m} p(x_1, \ldots, x_m) \log \frac{p(x_1, \ldots, x_m)}{p(x_1, \ldots, x_{m-1}) p(x_m)}, \tag{3}$$

measures the average information about the variable X_m contained in the $m-1$ variables $X_1, \ldots, X_{m-1}$.

For a stochastic process, $\{X_i\}$, characterized by the joint probability function, $p(x_1, \ldots, x_m)$, the entropy rate can be defined as

$$h = \lim_{m \to \infty} \frac{1}{m} H(X_1, \ldots, X_m), \tag{4}$$

where $H(X_1, \ldots, X_m)$ is the joint entropy of the m variables $X_1, \ldots, X_m$,

$$H(X_1, \ldots, X_m) = -\sum_{x_1 \in \Psi_1} \cdots \sum_{x_m \in \Psi_m} p(x_1, \ldots, x_m) \log p(x_1, \ldots, x_m). \tag{5}$$

When the variables X_i are taken as variables of an m-dimensional dynamical system, equation (4) defines the Kolmogorov–Sinai entropy [15]. If only a scalar time series, $\{z(t)\}$, generated by the dynamical system is available, time delayed values of the measured series can be used as the variables X_i,

$$X_i = z(t + (i-1)\tau), \tag{6}$$

where τ is the time delay. For a stationary dynamical process, the marginal redundancy becomes a function of the dimension, m, and the delay, τ, but independent of time, t,

$$R'(m, \tau) \equiv R'[z(t), z(t+\tau), \ldots, z(t+(m-2)\tau); z(t+(m-1)\tau)]. \tag{7}$$

The entropy rate, h, can be approximated as

$$h \approx \frac{R'(m, 0) - R'(m, \tau)}{\tau}, \tag{8}$$

for large enough m and some range of τ. Unfortunately, the accuracy of the approximation of h strongly depends on the amount and the noisiness of data available. With large amounts of clean data a fine partition of the phase space and therefore a better approximation of the probability distribution function is obtainable. However, with limited amounts of data contaminated by noise the estimation of the Kolmogorov–Sinai entropy, h, is practically impossible.

Since the exact entropy rate cannot be estimated, Paluš proposed a ''coarse-grained entropy rate'', CER [13]. CER is not meant as an estimate of the exact entropy rate, although CER and h both measure the predictability and regularity of analyzed time series. Instead, CER is useful as a statistic for the comparison of different datasets measured in the same experimental conditions [13].

CER is coarse-grained in space, because the partition of the phase space in estimating the probability distribution functions is only as fine as a length of the time series allows. CER is limited also in time, since the limit $m \to \infty$ cannot be calculated due to the finite length of the measured series. Based on equation (8), CER can be defined as [13]

$$h^{(0)} = \frac{R'(m, \tau_0) - R'(m, \tau_1)}{\tau_1 - \tau_0}. \tag{9}$$

This definition is directly related to the estimate of the Komogorov–Sinai entropy from the slope of linearly decreasing marginal redundancy [14]. However, in many applications $R'(m, \tau)$ decreases neither linearly nor monotonically and different choices of τ_o and τ_1 can significantly change the estimated value of $h^{(0)}$. A numerically more stable definition of CER [13] is

$$h^{(1)} = \frac{R'(m, \tau_0) - \|R'(m)\|}{\|R'(m)\|}, \tag{10}$$

where $\|R'(m)\|$ is a norm of the marginal redundancy,

$$\|R'(m)\| = \frac{\sum_{\tau=\tau_0}^{\tau_{max}} R'(m, \tau)}{\tau_{max} - \tau_0}, \tag{11}$$

in which the integral $\int R'(m, \tau)\, d\tau$ which measures the area under the curve of $R'(m, \tau)$ is approximated.

In equation (11), the lag τ_0 is usually set to zero and τ_{max} is selected so that $R'(m, \tau) \approx 0, \tau \geqslant \tau_{max}$. Dimension $m = 2$ to 3 is sufficient in many applications [13].

CER $h^{(1)}$ is a dimensionless quantity and its values are bounded to the interval $[0, \tau_{max}]$, when $\tau_0 = 0$. Values close to the lower bound of the interval are obtained for linear deterministic processes, such as undamped harmonic oscillations, whereas values close to the upper bound are obtained for random processes.

Similarly to the general coarse-grained entropy rate in equation (10), one can define a ''linear entropy rate'', LER [13], for which the absolute value of the autocorrelation function, $A(\tau) = E[z(t)z(t+\tau)]$, is used instead of the marginal redundancy

$$\mathrm{LER} = \frac{|A(\tau_0)| - \|A\|}{\|A\|}. \tag{12}$$

Here $\|A\|$ denotes the norm

$$\|A\| = \frac{\sum_{\tau=\tau_0}^{\tau_{max}} |A(\tau)|}{\tau_{max} - \tau_0}. \tag{13}$$

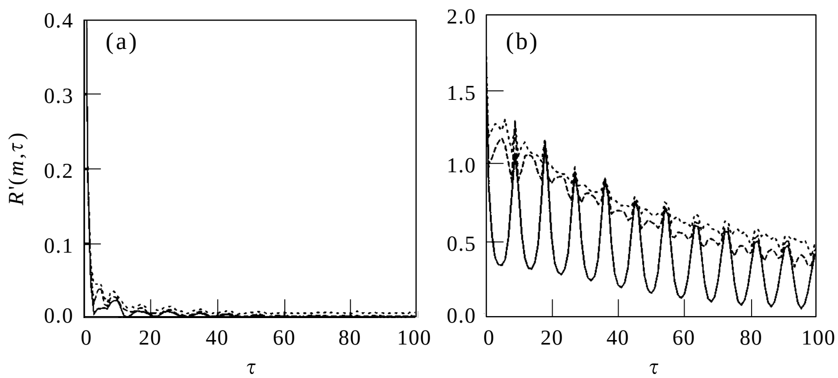

Figure 6. Marginal redundancies of the cutting component, F_c; (a) before chatter, at $a = 0{\cdot}3$ mm, and (b) during chatter, at $a = 1{\cdot}0$ mm. Different curves correspond to dimensions $m = 2$ to 4. Note the difference in vertical scale of the figures. ——, $m=2$; – – – –, $m = 3$; - - - -, $m = 4$.

Although defined in a similar way, CER [equation (10)] and LER [equation (12)] are not equivalent. Since general redundancy measures non-linear relations between the variables X_i, and autocorrelation reflects only their linear relations, CER is expected to be more sensitive to changes in the system dynamics than LER.

4. DETECTION OF CHATTER USING CER

In the investigation presented below we have used both the entropy rate, $h^{(1)}$ [equation (10)], denoted as CER, and the linear entropy rate, LER [equation (12)]. The minimum lag, τ_0, was set to zero and the lag step was $\Delta\tau = 1$ in units of sampling time. For the estimation of the probability distribution functions needed to calculate CER, marginal equiquantization [14] was applied with $Q = 4$ bins in each dimension.

First, experiments with cutting depth as the control parameter are discussed. Marginal redundancies of the cutting component, F_c, before and after the onset of chatter are shown in Figure 6. A high entropy rate is typical for chatter-free cutting [Figure 6(a)]. $R'(m, \tau)$ reaches values close to zero already at short lags, $\tau \approx 5$, indicating a rapid loss of information about previous process states. On the contrary, during chatter $R'(m, \tau)$ decreases slowly, oscillating with the frequency characteristic of chatter [Figure 6(b)]. The area under the curves of $R'(m, \tau)$ is larger in the latter case and the entropy rate is thus lower. The lower the entropy rate the greater the regularity and the predictability of the process.

The diagram in Figure 7 shows the dependence of CER(m) on the cutting depth, a, for the cutting component, F_c. The values of CER stay high during chatter-free cutting and drop below 10 during chatter. A similar sudden decrease of CER can be observed in various dynamical processes at the points of bifurcation from chaotic to periodic motion [16].

If CER is calculated by using marginal equiquantization [14], and if Q, τ_0, and $\Delta\tau$ are kept fixed, the value of CER depends on sampling time, t_s, dimension, m, number of points in the time series, N, and maximum time lag, τ_{max}. With $m = 2$ and upon assuming an appropriate sampling time, in our case $t_s = 0{\cdot}2$ ms, N and τ_{max} remain to be selected.

Figure 8 shows the influence of N and τ_{max} on the value of CER. In Figure 8(a), the maximum lag was set to either 20, 50, or 100, and all 30 000 points of the measured time series were used in the calculation. For convenience, CER was normalized by τ_{max}, which is CER's maximum possible value. As expected, the value of CER increases when the

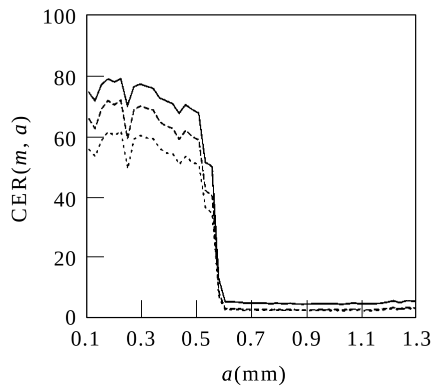

Figure 7. CER(m) of the cutting component, F_c, versus the cutting depth, a. Different curves correspond to dimensions $m = 2$ to 4 reading from top to bottom. A significant drop of CER values indicates the onset of chatter. $N = 30\,000$, and $\tau_{max} = 100$.

maximum lag is decreased. Nevertheless, chatter is in all cases detected by the drop of the normalized CER value below 0·2.

In Figure 8(b), $\tau_{max} = 20$ was kept fixed and the length of the time series, N, was varied. For $N = 1000$ and $N = 5000$ the first 1000 and 5000 points of the time series were chosen for the estimation of CER. The global dependence of CER on the cutting depth is not changed as N is reduced and chatter is easily detected. Although shorter time series lead to increased variability of CER values, especially before the chatter onset, false chatter detections do not occur.

For on-line applications the calculation of CER should be performed as fast as possible. On a standard PC-586 it takes 200 ms to calculate CER with $Q = 4$, $m = 2$, $N = 1000$, $\tau_{max} = 20$, and 270 ms if the maximum lag is increased to $\tau_{max} = 50$. The efficiency of the calculation can be further increased if such instruments are used in the measurement setup that are capable of calculating the autocorrelation function fast, possibly with the help of the fast Fourier transform. In this case, the linear entropy rate, LER, can be applied instead of CER.

Figure 9 shows the influence of N and τ_{max} on LER versus the cutting depth, a. LER was normalized with $\tau_{max}/2$ where the factor 1/2 was added due to numerical reasons.

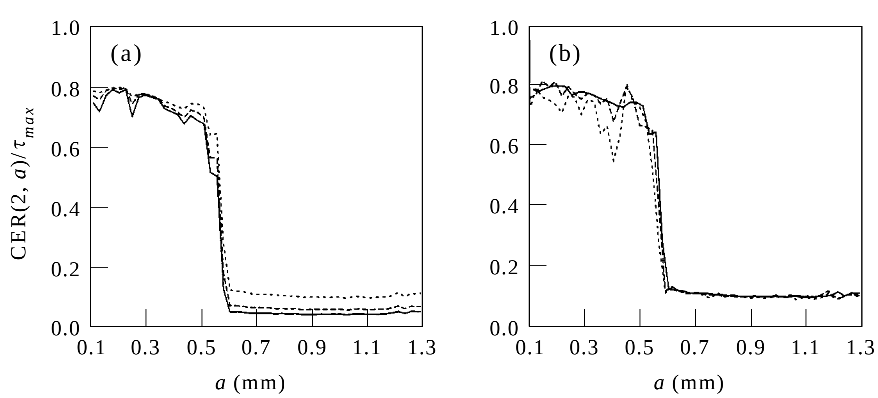

Figure 8. The influence of (a) the maximum lag, τ_{max}, and (b) the length of the time series, N, on the value of CER. For (a) $N = 30\,000$, and for (b) $\tau_{max} = 20$. Chatter can be easily identified in all cases. (a), τ_{max} values: —, 100; − − −, 50; - - - - -, 20. (b), N values: ——, 30 000; − − −, 5000; - - -, 1000.

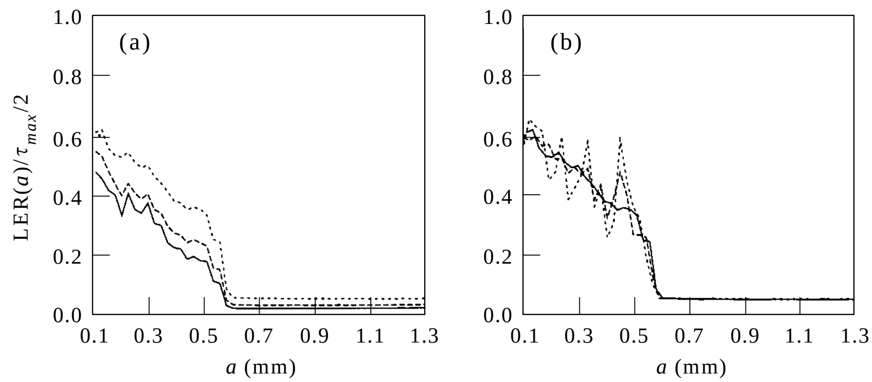

Figure 9. The influence of (a) the maximum lag, τ_{max}, and (b) the length of the time series, N, on the value of LER. For (a) $N = 30\,000$, and for (b) $\tau_{max} = 20$. $\text{LER}/\tau_{max}/2 < 0{\cdot}10$ reliably indicates chatter. Key as in Figure 8.

Conclusions similar to those for Figure 8 can be drawn. The normalized LER increases as the maximum lag is decreased [Figure 9(a)]. The drop of normalized LER value below 0·1 indicates chatter, although the drop is less significant for longer lags τ_{max}. For shorter time series the values of LER exhibit increased variability [Figure 9(b)], but chatter is never falsely detected.

Comparison of CER and LER (Figures 8 and 9) shows that the former is a more sensitive and robust characteristic for chatter detection. This is to be expected, since marginal redundancy measures general, non-linear correlations between the lagged variables, while autocorrelation measures only their linear correlations.

Similar results can be obtained with the other two components of the main cutting force, F_f and F_t. CER$(2, a)$ and LER(a) for all three components are shown in Figure 10. $N = 1000$ and $\tau_{max} = 50$ were chosen to ensure short calculation times needed in real-time applications. The drop of CER is least significant for the feed component, F_f [Figure 10(a)], while in the case of LER [Figure 10(b)], the least significant drop is found for the cutting component, F_c. According to Figure 10, the thrust component, F_t. seems to be the most appropriate for chatter detection using either CER or LER, though the other two components may also be effectively applied. In general, $\text{CER}/\tau_{max} = 0{\cdot}2$ and $\text{LER}/\tau_{max} = 0{\cdot}05$ could be used as suitable thresholds for reliable chatter detection.

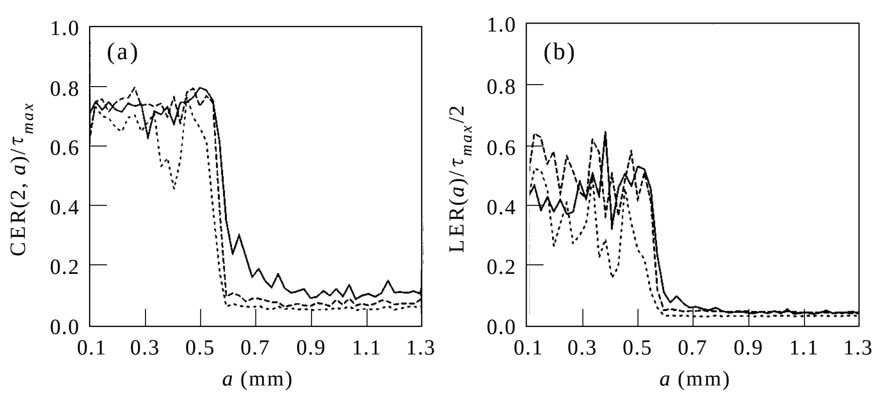

Figure 10. Dependence of (a) CER and (b) LER on the cutting depth, a, for all three components of the main cutting force, **F**. $N = 1000$ and $\tau_{max} = 50$. ——, F_f; – – –, F_t; - - -, F_c.

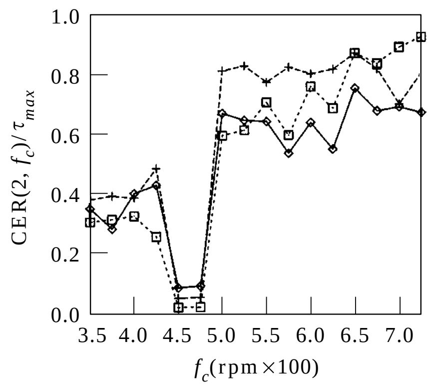

Figure 11. Dependence of CER on the turning frequency, f_c, for all three components of the main cutting force, **F**. Chatter is correctly detected at $f_c = 450$ rpm. $N = 30\,000$ and $\tau_{max} = 100$. Key as in Figure 10.

The results presented so far correspond to the first set of experiments in which the cutting depth was used as the control parameter. In the second set of experiments, the turning frequency, f_c, was varied, while the rest of the cutting parameters were kept constant. Dependence of CER on the turning frequency for all three components of **F** is shown in Figure 11. Chatter was observed only at $f_c = 450$ rpm which is correctly detected by $\mathrm{CER}/\tau_{max} < 0{\cdot}2$. Cutting at other f_c was chatter-free. In addition, pre-chatter cutting at $f_c \leqslant 400$ rpm is characterized by a relatively low value of CER as compared to CER values at $f_c \geqslant 500$ rpm. Again, the thrust force, F_t, appears to be the most appropriate for chatter detection when using CER.

5. CONCLUSIONS

A new method for chatter detection has been presented. The method is based on different dynamical properties of chatter-free cutting and cutting accompanied by chatter. A significant distinction between the dynamics of these two cutting regimes can be measured by various characteristics [10]. Among them the coarse-grained entropy rate, CER [13], was found to be particularly useful when measured time series of process variables are short and noisy.

Experiments with single point turning of cylindrical workpieces were performed. Either cutting depth or turning frequency were applied as control parameters. Slow and smooth increase of the cutting depth resulted in transition from chatter-free cutting to chatter. The increase of turning frequency caused the transition from chatter-free cutting to chatter and again to chatter-free cutting regime. CERs were calculated based on measured signals of cutting forces. A high CER value is shown to be typical of chatter-free cutting, while a low CER value is typical of chatter. A significant drop of the CER value indicates the onset of chatter. The transition from chatter-free cutting to chatter resembles a type of bifurcation, since similar behavior of the entropy rate can be found also in other dynamical processes at the points of bifurcation from chaotic to periodic motion [16]. A similar jump of the entropy rate is characteristic also for various phase transformations related to transitions from random to self-organized states of matter.

Beside the qualitative insight into the dynamics of cutting, CER provides a quantitative measure of the properties of cutting state. The normalization limits CER values to a range between zero and unity. This is suitable in particular if a threshold, independent of the cutting parameters, is desired. According to our experience, the normalized values of CER below 0·2 reliably indicate chatter, regardless of the cutting conditions.

The optimal value of the threshold might slightly vary for different machine tools. The smoothness of the transition from chatter-free cutting to chatter certainly depends on the compliance of the machine tool structure. If the structure is more compliant the transition will be smoother and the drop of CER value will be less explicit. Nevertheless, due to the nature of its dynamics, chatter is characterized by a lower value of entropy rate than chatter-free cutting, regardless of the machine tool and type of the transition between the two cutting regimes. In fact, the stronger and more pronounced the chatter, the lower the CER value. In the case of compliant structure and absence of a significant drop of the CER value, a trend of CER towards low values can still signal the approaching chatter.

The chatter detection method presented in the article is shown to be robust with respect to the time series length and the maximum time lag which are both important for temporal efficacy of the calculations of CER. With suitably chosen numerical parameters CER can be calculated within 300 ms on a standard PC-586. If measurement instruments are capable of fast calculation of autocorrelation function, the linear entropy rate, LER[13], can be used instead of CER. However, CER appeared to be more appropriate for chatter detection then LER.

The efficiency of the method depends also on the sampling rate. In the case of too fast sampling, longer time series are required which prolongs the necessary calculations, whereas too slow sampling does not allow correct capturing of the cutting dynamics. Eventual non-stationarity of the cutting dynamics is not fatal for the estimation of CER. As shown in the article, CER can be satisfactorily estimated also when using relatively short time series, during which the stationarity condition for the time delay reconstruction [equation (6)] is easier to meet.

In conclusion, the presented method for chatter detection based on coarse-grained entropy rate offers a quantitative characteristic that is easy to calculate and has a threshold independent of cutting conditions. The method is readily applicable for on-line chatter detection in an industrial environment.

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