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ORIGINAL ARTICLE

Permutation entropy based real-time chatter detection using audio signal in turning process

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Abstract Machine tool chatter is an unfavorable phenomenon during metal cutting, which results in heavy vibration of cutting tool. With increase in depth of cut, the cutting regime changes from chatter-free cutting to one with chatter. In this paper, we propose the use of permutation entropy (PE), a conceptually simple and computationally fast measurement to detect the onset of chatter from the time series using sound signal recorded with a unidirectional microphone. PE can efficiently distinguish the regular and complex nature of any signal and extract information about the dynamics of the process by indicating sudden change in its value. Under situations where the data sets are huge and there is no time for preprocessing and fine-tuning, PE can effectively detect dynamical changes of the system. This makes PE an ideal choice for online detection of chatter, which is not possible with other conventional nonlinear methods. In the present study, the variation of PE under two cutting conditions is analyzed. Abrupt variation in the value of PE with increase in depth of cut indicates the onset of chatter vibrations. The results are verified using frequency spectra of the signals and the nonlinear measure, normalized coarse-grained information rate (NCIR).

Keywords Metal cutting · Chatter · Time series · Permutation entropy

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1 Introduction

Metal cutting is a complex nonlinear dynamical process. The machine, the cutting tool, and the work piece form a complex system which has infinite number of degrees of freedom. The cutting process under dynamical conditions can behave in different ways for different modes of vibration. Instability of cutting process causes self-excited large-amplitude vibrations of the tool relative to the work piece. This phenomenon, known as chatter, adversely affects the performance and efficiency of the cutting process, quality of the product and produces high level of noise. This has negative influence on surface finish and dimensional accuracy of the work piece, tool life, and even machine life. Hence, it is important to detect the occurrence of chatter at an early stage so that corrective measures can be adopted by changing the cutting conditions. Various factors leading to chatter onset are increase in depth of cut, variation in cutting speed and variation in feed rate.

Extensive research using different sensor signals and various signal processing techniques has been performed on chatter detection. Signals acquired from force sensors [1, 2], accelerometers [3], spindle drive current [4], audible sound signal from a microphone [5], acoustic emission signals [6] are used for study and analysis of cutting dynamics. Factors that decide the sensor selection are bandwidth, sensitivity, signal to noise ratio, and sensor placement. Audio signal captured by a microphone is found to be the ideal compromise among these sensors [7]. A microphone can effectively be used for chatter detection as the acoustic pressure during machining is proportional to the displacement of the tool [8]. Unlike other sensors, the use of a microphone is simple and does not involve any positioning problem. Audio signals are already in use with commercial software like Harmonizer [9].

Linear signal processing techniques used for chatter detection are power spectral analysis of cutting force [7, 10], wavelets analysis [3], and statistical characterization [11]. It is already established that turning process on a lathe exhibits low-dimensional chaos [12]. Onset of chatter is always accompanied by development of synchronized oscillations which results in increased regularity or drop in entropy rate [13, 14]. Therefore, quantitative measure for detection of dynamical changes can be effectively used for detection of chatter onset. Some of the important and effective techniques to detect dynamical changes in real-world systems are recurrence plots [15] and recurrence quantification analysis [16, 17], cross correlation sum analysis [18], and nonlinear prediction analysis [19]. Coarse-grained entropy rate (CER) [11], coarse-grained information rate (CIR), and entropy from power spectrum [13] of appropriate signals are proposed for automatic chatter detection. These nonlinear methods are based on phase space reconstruction by quantifying the distance between nearest neighbors in phase space. The phase space reconstruction of the time series data is computationally expensive as it requires calculation of two parameters—time delay and embedding dimension. Most of these methods give significant results when the time series is simulated from low-dimensional dynamical systems and fails or misleads in the presence of noise. Hence, real-world time series analysis of the data requires preprocessing for noise elimination. Furthermore, embedding dimension and time delay are critical parameters in reconstruction of state space and the computation is time-consuming which restricts its application on real-time basis. Hence, it is essential to have a very fast algorithm which can process the data at the same rate at which it is acquired.

Here, we propose the use of a fast nonlinear analysis technique viz. permutation entropy (PE) [20], to detect the onset of chatter from audio cutting signal captured using unidirectional microphone. PE is a complexity measure which is robust against dynamical as well as observational noise [20]. It is a regularity statistic which relies on the order relations between neighboring values of a time series and is applicable to any real-world data. It gives quantitative information about the complexity of a time series. Thus, the variation of PE as a function of time can effectively indicate dynamical change. With the onset of chatter, strongly synchronized vibrations buildup and these chatter vibrations present itself in the dynamics as a lowering of dimensionality of the system and thereby an increase in the predictability of the system dynamics [21, 22]. According to the properties of PE and chatter dynamics, PE is expected to show relatively no change during chatter-free cutting. As the chatter vibrations develop during the cutting process, due to the increased predictability of the system dynamics PE values are expected to decrease.

In this paper, we demonstrate the effectiveness of PE in detecting the onset of chatter in two turning processes (a) sudden increase of depth of cut (b) continuous increase of depth of cut on mild steel work pieces. In both the cases, the acquired audio signals are recorded in a standard PC using a sound card. These signals are directly subjected to PE analysis. The results show that PE drops at the onset of chatter in both the cases. The results are verified using normalized coarse-grained entropy rate (NCIR) [13] proposed earlier for chatter detection, calculated from mutual information of the fluctuations of the recorded signal. The results of our study show concurrence of a drop of PE with increase in NCIR. Calculation of NCIR demands state space reconstruction whereas PE analysis could be done directly on the acquired signal. Unlike other nonlinear measures, PE analysis is computationally very fast which makes it an ideal choice for online chatter detection.

2 Permutation entropy

Computation of PE is based on comparison of neighboring values in the time series of any dynamical variable of a system. It has been shown that any continuous time series representing a dynamical system can be mapped onto a symbolic sequence [20, 23, 24]. According to the embedding theorem, any arbitrary time series $X = \{x_1, x_2, \ldots\ldots, x_T\}$ can be mapped on to an n dimensional space with vectors $X_i = \{x_i, x_{i+\tau}, x_{i+2\tau} \ldots\ldots, x_{i+(n-1)\tau}\}$ where n is the embedding dimension and τ is the delay time for embedding calculated using appropriate methods like false nearest neighbor calculation and first minimum of autocorrelation function [25]. For any arbitrary vector, X_i, the components are n number of real values of the time series $\{x(t), x(t+\tau), x(t+2\tau) \ldots\ldots, x(t+(n-1)\tau)\}$ from time instant t to '$t+(n-1)\tau$'. Assuming τ=1 [14], if the components of any arbitrary vector are arranged in ascending order $x(t+(j_1-1)) \leq x(t+(j_2-1)) \leq \ldots\ldots \leq x(t+(j_n-1))$, it will represent a pattern of evolution. Whenever an equality occurs $x(t+(j_1-1)) = x(t+(j_2-1))$, components are arranged according to their occurrence represented by the value of j as $j_1<j_2$ so that $x(t+(j_1-1)) = x(t+(j_2-1))$ can be arranged as $x(t+(j_1-1)) < x(t+(j_2-1))$. Therefore, any vector X_i can be uniquely mapped onto a pattern which will be one of the $n!$ possible permutations which can be considered as a symbol. Thus, the reconstructed trajectory in the n dimensional space represents a symbol sequence [23]. The probability distribution of each pattern π_i can be represented as

$$p(\pi_i) = \frac{\#\{t | t \leq T - n, (x_{t+1,\ldots\ldots,}x_{t+n}) \text{ has type } \pi_i\}}{T - n + 1} \quad (1)$$

Permutation entropy of order $n \leq 2$ is defined as the Shannon entropy of the $n!$ patterns or symbolic sequences and can be written as

$$H(n) = \sum_{i=1}^{n!} p(\pi_i) \ \log(p(\pi_i)) \quad (2)$$

where the sum runs over all $n!$ permutations or sequences. $H(n)$ lies between 0 and $\log(n!)$. For increasing or decreasing sequence of values, $H(n)=0$, whereas for random series where all $n!$ possible permutations appear with the same probability, $H(n) = \log(n!)$. For a time series representing some dynamics, $H(n)<\log(n!)$. Therefore, normalized PE per symbol of order n is given by $H(n)/\log(n!)$. Thus, PE characterizes the system dynamics, with low values indicating regular behavior. Any increase in PE value will thus represent a tendency of increase in irregularity in the dynamics. For detection of dynamical changes from time series, it is first partitioned into non-overlapping windows of suitable length T. PE for each window is calculated using Eqs. 1 and 2. Any change in the dynamics of the system will be reflected in the variation of PE with respect to a moving window. For a reliable estimation of PE, the window length T should be greater than $n!$ [20]. The order of PE should not be too small as this will not give enough number of distinct states. Also, too-large values of order n will demand large values of window size which will not effectively detect dynamical changes and also will create memory restrictions. Optimum values of order of PE are reported to be around 5 to 8 [20, 23]. In our analysis of chatter detection, window sizes of 1,024 and 2,048 showed similar results for PE of order 5, 6, and 7. Therefore, PE of order 6 is used for a window size of 1,024 samples. PE is found to effectively detect bifurcation-like transitions in model systems, and real-world dynamical systems like epileptic seizure detection from EEG data, voiced sound from audio signal data and also in tool flute breakage detection in end milling. Chatter is a similar dynamical transition where the low-dimensional chaotic behavior of normal cutting process changes to a more regular behavior where powerful synchronized oscillations near one natural frequency of the system build up. This significantly increases the mutual dependence of the characteristic variables at successive times thereby increasing the signal regularity and predictability. PE, as any other entropy, measures the randomness of a given system with added benefits of computational efficiency, robustness to dynamical and observational noise. Hence, PE is expected to decrease with onset of chatter.

3 Experimental set up and data acquisition

Single-point turning experiments without coolants are performed on a lathe at a feed rate of 0.06 mm per rev and 560 rpm. Samples of work pieces made of mild steel are prepared on a three-phase, 3.7 kW, 1,400 rpm PSG heavy-duty lathe using CNMG 120408 PM carbide inserts with standard tool holder. Figure 1 shows the experimental set up. The audio signals are captured using unidirectional microphone CSM-990, AHUJA, with frequency response 20–18,000 Hz. The microphone is mounted on a stand placed on the compound rest of the carriage of the lathe machine so that it moves along with the tool. The distance of the microphone from the work piece and the tool are maintained at 10 mm and 40 mm respectively and is covered with an absorptive material so that the acquired signal is not affected by the chip. Even though cutting force is an important variable for chatter detection and sensors like Kistler dynamometers have been developed to measure cutting force accurately, our study explores the possible use of a simple, low-cost method using audio signals for detecting chatter vibrations during machining. As the study aims at process monitoring through qualitative detection of synchronized large-amplitude vibrations, rather than measuring, no particular efforts are made towards calibration of sensor signals.

The experiments are carried out in two different cutting conditions (a) a 403.2-mm-long work piece is machined with 0.1 mm depth of cut for a length of 109.8 mm. The depth of cut is suddenly changed to 2.6 mm and is maintained for the next 293.4 mm. (b) A conical work piece of 171.2 mm length and initial diameter of 58 mm is machined with continuous increase in depth of cut from 0 to 0.8 mm. The audio signals are captured using unidirectional microphone CSM-990, AHUJA, with frequency response of 20–18,000 Hz. This signal is recorded in a standard PC using a sound card with data preprocessing of

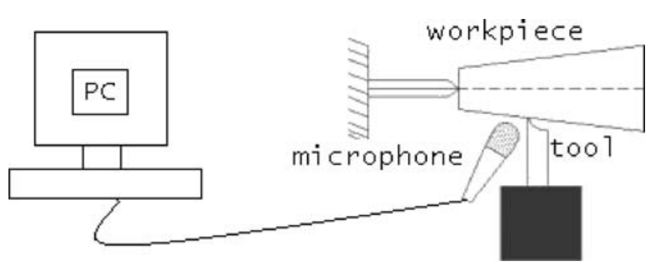

Fig. 1 Experimental set up

low-pass anti-aliasing. These signals are sampled at 11 kHz to generate the time series. Fifteen records are acquired for each cutting process and the corresponding time series are used for PE analysis. The program used for the PE analysis is developed by our group.

4 Results and discussion

The proposed method of chatter detection is verified on two types of cutting data. In each case, PE analysis is carried out on the acquired signals. For this, the time series is first partitioned into non-overlapping windows of 1,024 samples acquired within a time span of 93.1 ms. Variation of PE with respect to moving windows is used for detection of onset of chatter.

In the first experiment, a constant depth of cut of 0.1 mm is maintained up to a length of 109.8 mm of the work piece and suddenly changed to 2.6 mm at this point. Above this point, constant depth of cut of 2.6 mm is maintained up to a length of 403.2 mm. The sampled audio signal is converted to a time series of 800001 samples corresponding to a length of 403.2 mm. The time series is partitioned into non-overlapping windows of 1,024 samples. PE value is calculated for every window. Figure 2 shows the variation in PE with respect to length of the work piece. For a length of work piece below 109.8 mm corresponding to 0.1 mm depth of cut, it can be observed that there is no significant change in dynamics as indicated by PE values. Between 110.11 and 113.7 mm length of the work piece, a sharp decrease in PE value is observed. This drop in PE indicates increase in regularity of the dynamics thereby indicating the onset of chatter. Above 113.7 mm, PE value fluctuates within a large scale compared to the chatter-free region. The time required for the detection of this change can be calculated from the data acquisition time and calculation time of PE. With the sampling rate of 11 kHz, the data acquisition time of one data point is 91 μs. The time required for estimating PE values of one window is of the order of nanoseconds and can be neglected compared to the time required for acquiring the corresponding data points. The sharp decrease in PE value is observed between windows 213 and 220. These seven windows correspond to 7,168 samples. Therefore, the change in dynamics can be detected within 652 ms. Similar results are obtained with the recordings of other trials also. To test the statistical significance of difference in PE value of pre-chatter and chatter regions, a one-way ANOVA test is used (Matlab's ANOVA routine). The mean, standard deviation, and p values for all the cases are given in Table 1. From the statistical analysis, it is observed that p values of all the cases are found to be less than 1e−15, indicating that the null hypothesis of the two samples of pre-chatter PE and chatter PE coming from distributions with equal means should be rejected. From these results, a simple threshold for PE of sudden change in depth of cut can be set at a value of 0.8620.

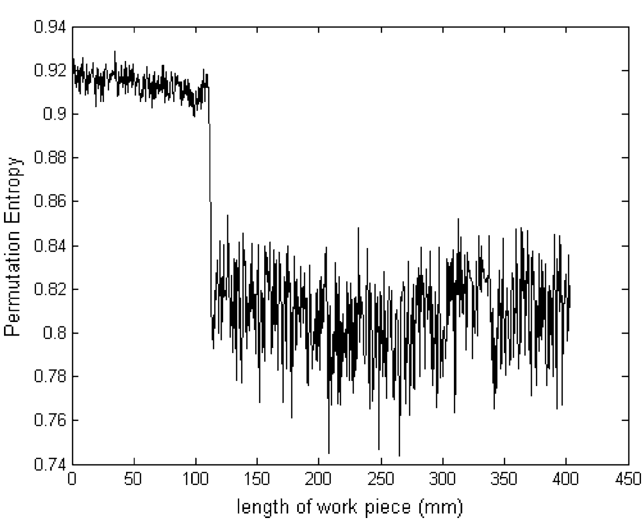

Fig. 2 Variation in PE with respect to length of the work piece for sudden change in depth of cut from 0.1 to 2.6 mm

The frequency spectrum of data with respect to length of the work piece is shown in Fig. 3. The spectra for a length 112.9 mm of the work piece do not contain any dominant peaks. Above this point, the spectra contain more number of dominant peaks. The development of harmonic peaks is indicative of more regular behavior which in turn represents the presence of chatter vibrations. The above-results are also verified using NCIR [14]. This is a coarse-grained estimate of the mutual information of a time series with its delayed values. For a time series $x(t)$ and its time delayed series $x(t+\tau)$, CIR is defined as the norm of mutual information and is given by the equation

$$\mathrm{CIR} = |I(x(t);x(t+\tau))| = \frac{1}{\tau_{\max}} \sum_{\tau=\Delta\tau}^{\tau_{\max}} I(x(t);x(t+\tau))\ \Delta\tau \quad (3)$$

The maximal time delay $\tau_{\max}$ is chosen such that $I(x(t):x(t+\tau)) \approx 0$ for $\tau \geq \tau_{\max}$. CIR values are bounded between 0 and log (Q), where Q represents the number of bins used for probability estimation. For convenience, CIR is normalized using log(Q). For highly regular and thereby predictable systems, NCIR is close to 1 whereas for irregular systems it is close to 0.

The software migram from CRP toolbox [26] is used to calculate $I(x(t);x(t+\tau))$ of Eq. 3 for CIR. Maximal time delay of 50 and embedding dimension of 2 are used for NCIR calculation [11, 13]. Figure 4 shows the variation of NCIR with respect to length of the work piece. For the initial range of cutting below the length of 109.8 mm of the

Table 1 Results of one way ANOVA test for sudden change in depth of cut

Trials	Mean		Standard deviation		p value* (1e−15)
	Pre-chatter	chatter	Pre-chatter	chatter	
Trial 1	0.916	0.8161	0.0056	0.0145	0
Trial 2	0.9164	0.8216	0.0052	0.0153	0
Trial 3	0.9164	0.8136	0.0053	0.0184	0
Trial 4	0.916	0.8132	0.0054	0.0209	0
Trial 5	0.9181	0.8141	0.0036	0.0125	0
Trial 6	0.9149	0.811	0.0044	0.0207	0
Trial 7	0.9165	0.8185	0.0047	0.0157	0
Trial 8	0.9122	0.8126	0.004	0.0196	0
Trial 9	0.9141	0.8101	0.0048	0.0224	0.111
Trial 10	0.9121	0.8091	0.0043	0.015	0
Trial 11	0.9126	0.8089	0.0054	0.0175	0
Trial 12	0.9137	0.801	0.004	0.0136	0
Trial 13	0.9107	0.8135	0.0037	0.0151	0
Trial 14	0.9065	0.795	0.005	0.0211	0
Trial 15	0.9097	0.7957	0.006	0.017	0

work piece the NCIR values remains at low values. The depth of cut is maintained at 0.1 mm in this range. At a length of 110.9 mm, there is a steady increase in the NCIR values for a small region up to a length of 115.1 mm. Above this point, the NCIR values remain in the higher range with larger fluctuations. Increase in NCIR values confirms the presence of chatter vibrations as indicated by change in PE values.

Similar analysis is carried out on a second set of data where the depth of cut is continuously varied from 0 to 0.8 mm over a 171.2-mm-long work piece thereby slow and smooth increase in depth of cut is maintained throughout the cutting process. Figure 5a and b shows the variation in PE with respect to depth of cut from 0 to 0.4 mm and from 0.4 to 0.8 mm, respectively. It can be observed from Fig. 5a that the PE values do not undergo any drastic variation along this range of depth of cut. It is evident from this figure that there is no significant change in the system dynamics. In Fig. 5b, a sudden drop in PE value can be observed at 0.46 mm depth of cut. This change in PE value indicates a sudden change in dynamics to more regular nature and thereby onset of chatter. Above this point, PE values increases and reaches almost equal to previous levels. This behavior is not sustained for long and is soon followed by sharp jumps indicating bursts of chatter up to 0.49 mm. Again, there is a slow increase in PE to values comparable to or even slightly higher than that of the chatter-free region. Thus, the dynamics is regained slowly after short bursts of chatter. The sudden drop in PE value occurs within an interval of time required for acquiring 5,120 samples which corresponds to 466 ms. The chatter detection speed of PE at this sampling rate is considerable

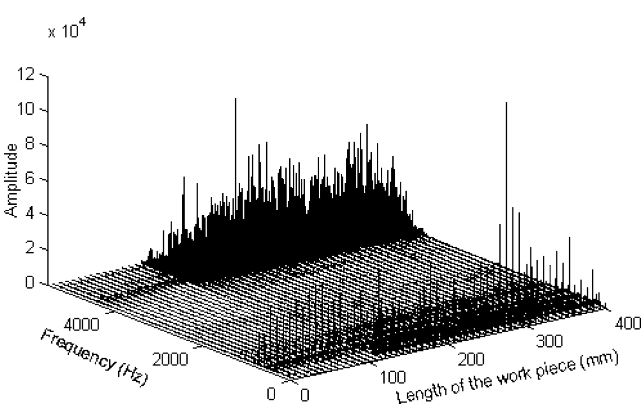

Fig. 3 Frequency spectrum in 3D perspective for sudden change in depth of cut from 0.1 to 2.6 mm

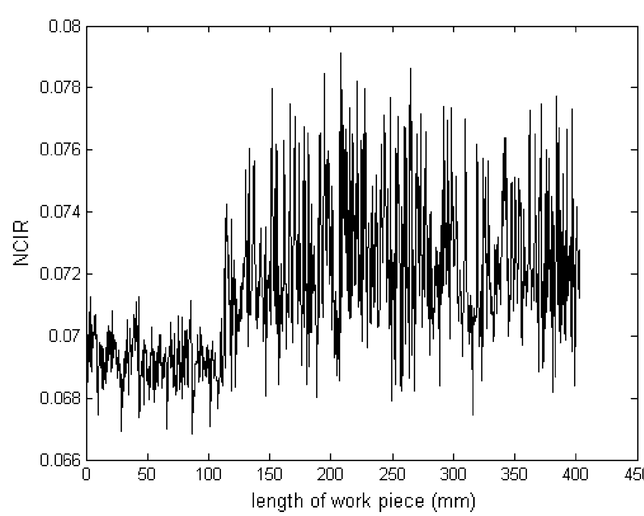

Fig. 4 Variation of NCIR with respect to length of the work piece for sudden change in depth of cut from 0.1 to 2.6 mm

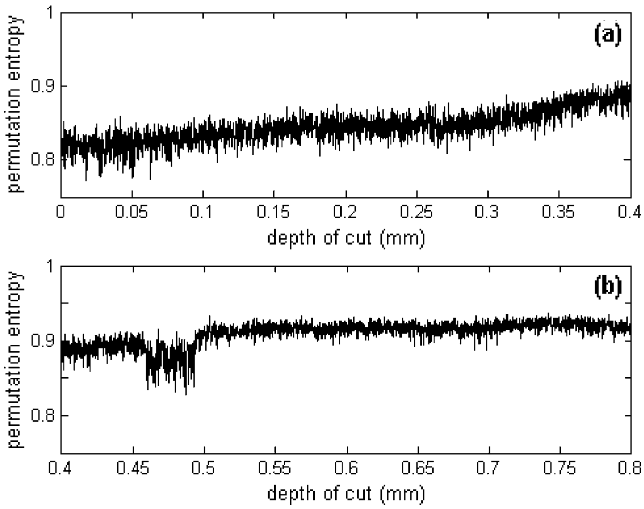

Fig. 5 **a** Variation in PE with respect to continuous increase in depth of cut from 0 to 0.4 mm. **b** Variation in PE with respect to continuous increase in depth of cut from 0.4 to 0.8 mm

for use with an online setup. Similar results are obtained with recordings of other trials also. The statistical significance of difference in PE value of pre-chatter and chatter regions is tested using one-way ANOVA routine of Matlab and the results are given in Table 2. p values of all the cases are found to be less than 0.05, indicating that the null hypothesis of the two samples of pre-chatter PE and chatter PE coming from distributions with equal means should be rejected. From the results of this statistical analysis, a simple threshold for PE for continuously increasing depth of cut can be set at a value of 0.86.

Table 2 Results of one way ANOVA test for continuous increase in depth of cut

Trials	Mean		Standard deviation		p value
	Pre-chatter	Chatter	Pre-chatter	Chatter	
Trial 1	0.8852	0.8737	0.0157	0.0115	0.0297
Trial 2	0.8905	0.869	0.0138	0.0065	0
Trial 3	0.891	0.865	0.0154	0.0096	0
Trial 4	0.8958	0.8833	0.02	0.0086	0.0346
Trial 5	0.8959	0.8876	0.0098	0.0041	0.0053
Trial 6	0.8955	0.885	0.0134	0.0073	0.0122
Trial 7	0.8885	0.8711	0.0144	0.0074	0.0003
Trial 8	0.8944	0.8711	0.0117	0.008	0
Trial 9	0.8929	0.8727	0.0142	0.0083	0.0001
Trial 10	0.8933	0.8743	0.0211	0.0081	0.0029
Trial 11	0.8973	0.878	0.014	0.0084	0.0001
Trial 12	0.8935	0.8798	0.0142	0.0089	0.0037
Trial 13	0.898	0.8662	0.0206	0.0088	0
Trial 14	0.8934	0.8845	0.0138	0.006	0.0292
Trial 15	0.8941	0.8774	0.0135	0.0085	0.0004

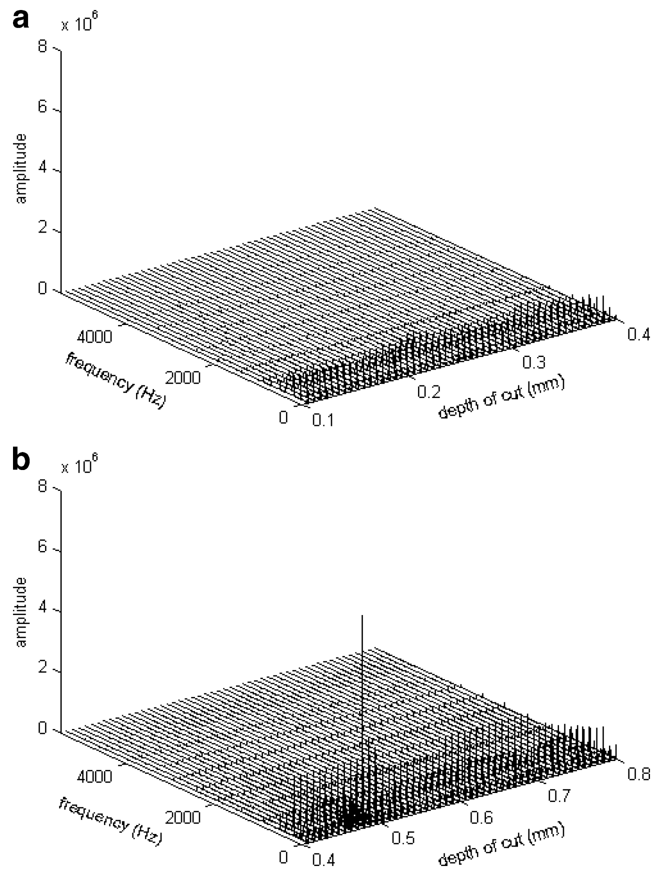

Fig. 6 **a** Frequency spectra with respect to continuous increase in depth of cut from 0 to 0.4 mm. **b** Frequency spectra with respect to continuous increase in depth of cut from 0.4 to 0.8 mm

Figure 6a shows the frequency spectra with respect to depth of cut varying from 0 to 0.4 mm and Fig. 6b that of 0.4 to 0.8 mm. The spectra in Fig. 6a do not contain any strong peaks which is typical of chatter-free dynamics. It is

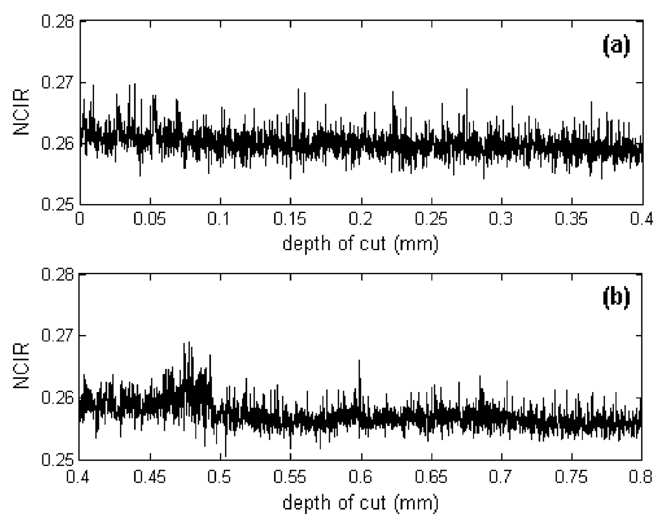

Fig. 7 **a** Variation in NCIR with respect to continuous increase in depth of cut from 0 to 0.4 mm. **b** Variation in NCIR with respect to continuous increase in depth of cut from 0.4 to 0.8 mm

clear from Fig. 6b that at 0.46 mm depth of cut, the harmonic contents in the signal are more pronounced than in the other regions. This strong peak is very well indicative of chatter regime. Figure 7a shows the variation of NCIR for the above signal for depth of cut from 0 to 0.4 mm and Fig. 7b shows the variation of NCIR for depth of cut from 0.4 to 0.8 mm. It can be inferred from the figure that NCIR values show an increase at 0.46 mm depth of cut. This gives an indication of the increase in information and thereby an increase in the predictability which in turn shows the increased regularity in the dynamics. The increase of NCIR values in Fig. 7b confirms the change in dynamics indicated by the drop in PE in Fig. 5b.

5 Conclusion

In this paper, the application of permutation entropy for the detection of onset of chatter in turning using audible signal is verified. Experiments are conducted on two different cutting conditions, sudden step cut and taper cut. In both the cases, higher values of PE with small variations indicate chatter-free region. Here, the transition from chatter-free to chatter regime is indicated by a sharp drop in PE value. In the case of sudden change in depth of cut after the drop, PE values remains in the lower range with larger fluctuations. PE values of taper cut in the pre and post chatter regions are in the higher range compared to that around the chatter regime. The results of statistical analysis of the PE data of various trials are used to define thresholds for both cases of sudden change in depth of cut and continuous increase in depth of cut. Considering the variation of PE with the associated dynamics, it is suggested that for taking conclusive decisions, crossing of thresholds should be correlated with sudden drastic change in PE. Calculation of PE algorithm is conceptually simple and computationally very fast and it gives reliable results even in the presence of noise. Unlike conventional nonlinear techniques for detection of dynamical changes, PE analysis does not demand any preprocessing of data. This makes PE an effective measure for large data sets where there is no time for preprocessing and fine-tuning of the data. The results of PE analysis are confirmed using frequency spectrum and normalized coarse-grained information rate.

PE analysis of audible sound signal is a fairly low-cost, non-contact, and non-destructive technique which enhances its suitability for online detection of chatter without disturbing the machining process. This method of chatter detection can be applied on real-time turning process with the help of suitable control mechanism [27].

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