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DETERMINATION OF TRANSIENT AND STEADY STATE CUTTING IN FACE MILLING OPERATION USING RECURRENCE QUANTIFICATION ANALYSIS

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ABSTRACT

Typical face milling operation involves transient and steady state cutting phases. Identification and distinction of the cutting state will primarily help in understanding the fundamentals of forced vibration, deflection and dynamic stability in milling system at the beginning and end of a cutting pass. Such type of investigation has advantages in process planning, tool geometry optimization and on-line fault diagnosis. An effort to provide estimation of transient and steady state cutting has been made using Recurrence Quantification Analysis (RQA) of vibration signals. RQA is a novel nonlinear analytical tool. It starts with construction of recurrence plot using embedded dimension and time delay. The recurrence plot is than quantified resulting in RQA. Face milling of H11 chromium steel has been carried out at two different cutting conditions and analyzed. The resulting RQA parameters could identify and distinguish transient and steady state cutting.

Keywords: Face milling, transient cutting, steady state cutting, recurrence plots, recurrence quantification analysis.

1. INTRODUCTION

Face milling is a multipoint cutting operation which is widely employed in automobile, aircraft, and military industries. A typical cutting process in face milling involves both steady state cutting and transient cutting. In steady-state cutting, a cutter has fully entered the workpiece and so the radial depth of cut remains constant. In case of transient cutting, the cutter is at the position of entry, exit, or gap cutting for which the radial depth of cut varies with time. The transient-state cutting forces are quite different from those in the steady state. The time variation of cutting forces exhibited during transient cutting has a significant effect on the surface texture and dimensional accuracy of the machined parts. This characteristic is of particular importance for small workpieces in which the majority of cutting time is spent in transient cutting [1]. A general cutting force model is applicable to steady state cutting where in radial depth of cut is constant, entry angle into the workpiece is zero and there is no variation of process parameter. In order to extend the model to transient state cutting, a decomposition procedure is first applied to represent any milling operation with non zero entry angles by the combination of milling operations with zero entry angles. The decomposition procedure is followed by temporal discretisation; where in a transient cutting is represented by a series of steady-state cutting with different depths of cut, enabling the use of general model for its analysis [1].
Spindle motor current is widely used as indirect means of measurement of dynamic cutting force variation in face milling process. Using rms value of spindle motor current tool fracture index (TFI), a dimensionless ratio has been defined. The computation of TFI has been mentioned by G. D. Kim *et al* [2]. It has been used to make distinction between tool fracture, entry cutting, hole cutting, slot cutting and exit cutting. After the tool fractures, the TFI has a large value. The tool fracture index value did not become large during transient cutting, (entry and exit cut), and as cutting condition changed during machining, and also during hole and slot cutting. At entry, although there was momentary rise in the tool fracture index it quickly reduced to 1. This could exhibit distinction between tool fracture from an entry or exit cut [2].

Features from the feed-motor current signals have been used to recognize minor cutting edge fracture during end milling along with identification of entry/exit cuts with a robust algorithm consisting wavelet-based de-noising, discrete time-frequency analysis, FFT and second differencing [3].

Cutting mechanics at initial stage of peripheral milling has been precisely studied and found that the transient cutting mechanics changes cutting force magnitudes abruptly, with the tool advancement both in up milling and down milling of peripheral milling process which are different from steady state cutting [4].

As most of the studies have been conducted considering steady state cutting operations where in continuous chip formation with a reasonable constant load occurs or where, in various types of discontinuous chips are formed, with loads regularly repeating in cyclic patterns. This observation was found to be true for both theoretical and experimental studies [5-11]. In the paper [8] the phenomenon of the cutting tool starting to advance into the workpiece has been generally described and discussed with the aim of analyzing the influence of material properties on chip formation as well as the effect of selected cutting parameters (such as rake angle) on the cutting forces and hardness variation in the chip.

The transient beginning of machining and transition to steady-state cutting raised important questions that needed attention especially from metallurgical aspects regarding the physics behind the separation of material at the tip of the tool. Whether the new surfaces formed were by shear or by tensile stresses? Is it possible to correlate material damage with the crack opening mode at the tip of the tool? Is it possible to replace the commonly imposed (and often arbitrary) material separation criteria (based on a wide variety of concepts such as, critical effective strain, critical effective stress, distance tolerance ….. etc), by a new damage-based criterion?

On the basis of signal processing also the important questions can be asked as to whether there are any better techniques in distinguishing signals obtained at entry, exit and steady state cutting conditions. Most of the techniques available make general assumption of linearity although the signals obtained are basically nonlinear and non stationary. Present study focuses on distinguishing these states of cutting conditions by using a relatively novice tool which has been developed without these general assumptions. Vibration signals obtained during face milling are analyzed using nonlinear time series analysis called recurrence analysis. The recurrence quantification analysis helps in quantifying different states of cutting during face milling.

Significant research has been done on the basis of cutting forces [12-15] Cutting force measurements are commonly taken using a dynamometer mounted on a machining worktable. The physical characteristics of the dynamometer mounted on the worktable seriously limit the physical size of the workpiece. On the other hand, if the tool holder is mounted on dynamometer, it interrupts the change of cutting tools, and also such dynamometer are to be custom made which could be costly. Additionally, the cutting force-based methods often require complex signal processing techniques, like high-order time series models, and FFT, as well as time-frequency analysis, which result in a hindrance to real time application due to the computation time.

Measurement of cutting tool forces has been widely used to detect abnormalities in cutting conditions since the cutting forces are closely associated with tool and workpiece interaction [16-19]. The cutting process involves the generation of forces and motions that produce vibration and unquestionably contains most of the information. If a fault occurs, monitored vibration characteristics change, makes detection and classification of fault possible [16, 19].

Several methodologies have been proposed and used to analyse the data obtained from vibration measurement, from simple statistical analysis to strategies that consider vibration signal from cutting operation as chaotic nature and apply non-linear methods to obtain parameters like the Lyapunov exponent [20, 21].

In the present study, investigation of time series vibration signals obtained from face milling at entry, middle and exit position of work piece has been carried out. By applying nonlinear embedding methods and the recurrence plots (RP) technique to the corresponding time series, the changes in nonlinear dynamics underlying the milling process are indicated, and RQA parameters identified and distinguished to classify positions at which the cutting takes place.

The study proceeds with introduction of Recurrence plot in section 2.Section 3 describes the Phase Space Reconstruction carried out to find time delay and optimal dimension so as to construct the Recurrence Plot as described in section 4. Various metrics of RP are defined in recurrence quantification analysis in section 5. Section 6 describes the experimental set up. Section 7 elaborates results and analysis and conclusion are drawn in section 8.

2. RECURRENCE PLOT

Recurrence analysis is comparatively a new non linear technique developed by Eckmann *et al.* [22]. The technique has been successfully applied to different fields ranging from physiology to economics [23, 24]. Recently it has made forays into engineering field [25-27]. Recurrence Plot is a graphical tool based on Phase Space Reconstruction which begins with a time-delay embedding of the data.

3. PHASE SPACE RECONSTRUCTION

The changing state of a dynamic system can be represented by sequences of 'state vectors' in the phase space. Usually in a dynamic system a detailed analysis is possible when the equations of motion and all degrees of freedom 'n' are known. Unfortunately only a few quantities can be usually observed in a system. However from a theoretical point of view it is argued that it is possible to reconstruct the entire dynamics of a system from a relatively small number of observables; because the different degrees of freedom of a dynamic system interact with each other, the combination of all other components is concealed in each observable quantity through the main state vector components [22]. In experimental data, however, the practitioner does not typically have access to each of the system's state variables. Fortunately the embedding theorems [28], demonstrate how delayed copies of a single state variable can be used to generate pseudo-state vectors that preserve certain properties of the "true" underlying dynamical system. The process of embedding allows the practitioner to extract information from a single signal that would otherwise not be available.

Let x = {x (1), x (2)…. x (M)} be a 1-dimensional data vector x comprising M real numbers. From this single 1-dim data vector of length M, a family of new vectors is constructed, each having length n<M. The N new vectors X_i are constructed as follows:

$$X_i = \{x(i), x(i+d),..., x(i+(n-1)d\}$$

Where i =1 to n, d is the delay time and n is the embedding dimension. The number of new vectors is given by:

N = M-(n-1) d.

Each of these vectors will be of dimension n. With proper values of n and d this representation is topologically equivalent to the underlying n-dimensional system that produced the time series x. Therefore each unknown point of the phase space at time *i* is

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reconstructed by the delayed vector X_i in an *m*-dimensional space called the reconstructed phase space. There exist a variety of methods for choosing values of n and d.

The most often used methods are the Average Mutual Information Function (AMI) for computing the time delay d, as introduced by Fraser and Swinney in 1986 [29] and the False Nearest Neighbors (FNN) method for the embedding dimension n developed by Kennel *et al.* [28]. One chooses the first minimum location of the average mutual information function as d .The percentage of false nearest neighbors (FNN) is computed for each of the m values. The embedding dimension is said to be found for the first percentage of FNN dropping to zero. This percentage never reaches a true zero value because of presence of noise in the signal. Hence optimal n is chosen for minimum value of FNN. The embedding parameters and RQA analysis can be carried out using the Visual Recurrence Analysis (VRA) version 4.6 codes by Eugene Kononov, which is freely available on the web [32].

4. RECURRENCE PLOT CONSTRUCTION

Once the space phase is reconstructed recurrence plot is to be constructed. The Recurrence Plot (RP) is plotted as a matrix of points (*i, j*) where each point is said to be recurrent and marked with a dot if the distance between the delayed vectors $X(i)$ and $X(j)$ is less than a given threshold ϵ; the distance can be Euclidean or maximum or minimum. In general the threshold radius ϵ has to be chosen as small as possible, but a too small ϵ can lead one to miss some structure, if there is noise distortion. As each coordinate *i* represents a point in time, RP provides information about the temporal correlation of phase space points [30] [31]. Indeed each horizontal coordinate *i* in RP refer to the state of the system at *i* and each vertical coordinate *j* refers to the state in *j*. So if the point (*i, j*) is marked as recurrent, the state *j* belongs to the neighborhood centered in *i* of size ϵ; this means that the state of the system at time *i* has some 'similarity' with the state of the system at *j*.
To understand it better consider a simple time series data [33]:

$$a = \{1,2,3,3,0\}$$

It has five data points i.e. M=5. Select delay time d=1 and embedding dimension n=2. Then the total numbers of new embedded vectors are:
N = M-(n-1) d = 4
The new 4 embedded vectors are then defined as:

$a(1) = \{1,2\}$; $a(2) = \{2,3\}$; $a(3) = \{3,3\}$; $a(4) = \{3,0\}$
Next step is to calculate distance matrix $D = \{a(i, j)\}$

$$D = \begin{bmatrix} a(4,1) & a(4,2) & a(4,3) & a(4,4) \\ a(3,1) & a(3,2) & a(3,3) & a(3,4) \\ a(2,1) & a(2,2) & a(2,3) & a(2,4) \\ a(1,1) & a(1,2) & a(1,3) & a(1,4) \end{bmatrix}$$

Here the numbering of rows begins from bottom to top of the matrix. The distances are calculated using Euclidean norm. Some of the distances calculated are as given below:

$$a(4,1) = \sqrt{(3-1)^2 + (0-2)^2} = 2\sqrt{2}$$

$$a(2,4) = \sqrt{(2-3)^2 + (3-0)^2} = \sqrt{10}$$

The remaining distances are shown in 4x4 matrix

$$D = \begin{bmatrix} 2\sqrt{2} & \sqrt{10} & 3 & 0 \\ \sqrt{5} & 1 & 0 & 3 \\ \sqrt{2} & 0 & 1 & \sqrt{10} \\ 0 & \sqrt{2} & \sqrt{5} & 2\sqrt{2} \end{bmatrix}$$

$$= \begin{bmatrix} 2.8 & 3.2 & 3 & 0 \\ 2.2 & 1 & 0 & 3 \\ 1.4 & 0 & 1 & 3.2 \\ 0 & 1.4 & 2.2 & 2.8 \end{bmatrix}$$

The lower left entry corresponds to (i,j) = (1,1) and the upper right entry corresponds to (4,4). Figure-1 shows RPs corresponding to three different values of epsilon: ε = 1, 2, and 3, thus signifying the choice of threshold radius epsilon.

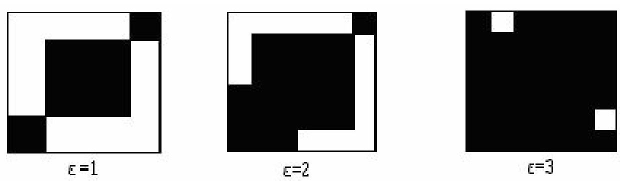

Figure-1. Recurrence plots for three different values of epsilon.

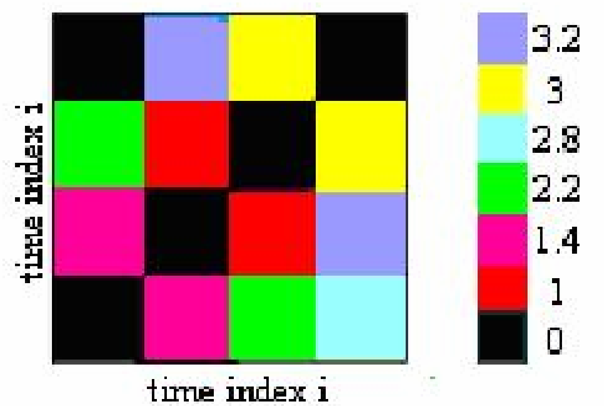

Figure-2. Contour plot corresponding to the distance matrix D (i,j).

Finally Figure-2 shows the contour plot of the D (i,j) matrix itself without considering threshold radius. All these RPs can be plotted using VRA software.

5. RECURRENCE QUANTIFICATION ANALYSIS (RQA)

Recurrence quantification analysis is a quantitative analysis tool which classifies and characterizes recurrence plots [30]. For quantitative analysis, following variables were defined:

Percent recurrence

Percent recurrence is the ratio of the number of recurrent states measured with respect to all possible states. Percent recurrence is given by

$$\%REC = 1/M^2 \sum_{i,j=1}^{M} R_{ij}.$$

Where R_{ij} are recurrence points and M are all the points obtained after calculation of time delay and embedding dimension and fixing of threshold radius. Embedded processes that are periodic have high percent recurrence value.

Percent determinism

Percent determinism is the percentage of recurrent points forming line segments parallel to the main diagonal to number of recurrence states measured. The presence of these lines reveals the existence of a deterministic structure.

$$\%DET = \frac{\sum_{i,j=1}^{M} D_{ij}}{\sum_{i,j=1}^{M} R_{ij}}$$

Where D_{ij} are all the points forming line segments parallel to the main diagonal.

Ratio

Ratio of percent determinism to percent Recurrence. It is useful to detect transition between states.

Trend

Trend is slope of line-of-best-fit through %recurrence as function of displacement from main diagonal. It detects non stationarity in the data.

Laminarity

Laminarity is the ratio of recurrence points forming vertical structures to all recurrence points. Laminarity is related to intermittency in the system.

Trapping time

Trapping Time is defined as the average length of the vertical structures in RP. It represents the average time in which the system is trapped in a specific state.

Maxline

Maxline is the longest line segment measured parallel to the main diagonal. A periodic signal produces long line segments, while short lines indicate chaos.

Entropy

It is Shannon entropy, entropy of the distribution of the length of line segments parallel to the main diagonal [31]. The entropy gives a measure of how much information one needs in order to recover the system. A low entropy value indicates that few information are needed to identify the system, in contrast, high entropy indicates that much information are required. The entropy is small when the length of the longest segment parallel to the diagonal is short and does not vary much. This has to be associated with information on determinism. High entropy is typical of periodic behavior while low entropy indicates chaotic behavior.
All these variables can be computed using VRA software.

6. EXPERIMENTAL SETUP

Experiments were conducted on a Universal Milling machine which has 5 HP spindle motor and 3 HP feed motor. It has speed range between 60 rpm to 830 rpm. It has three feed steps i.e. 22.5 mm/min, 30 mm/min and 60 mm/min. Machining was done under dry condition.
Workpiece material used in the experimental trials was H11 hot rolled Chromium steel. All the specimens were of rectangular cross section and with 60 X 100 X 22 mm dimensions.

The milling cutter and inserts used were of SECO R220.43-0063-07W and 07045 TN M16 373M, respectively.

Vibration signals were acquired using triaxial accelerometer which was mounted on bearing housing of the spindle. Figure-3 shows the experimental set up.

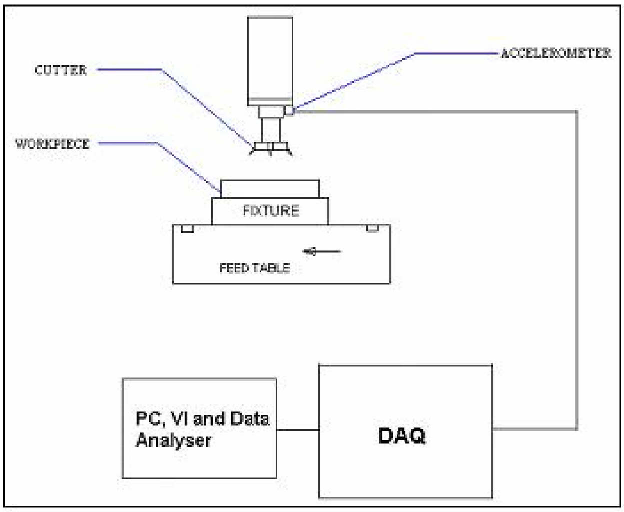

Figure-3. Experimental set up.

The PCI card NI 4472 along with LabVIEW 8 was used for data acquisition. Data was acquired at a sampling frequency of 5000 Hz and for time duration of 2 seconds. A simple block diagram in LabVIEW was used to acquire the vibration data and is shown in the Figure-4.

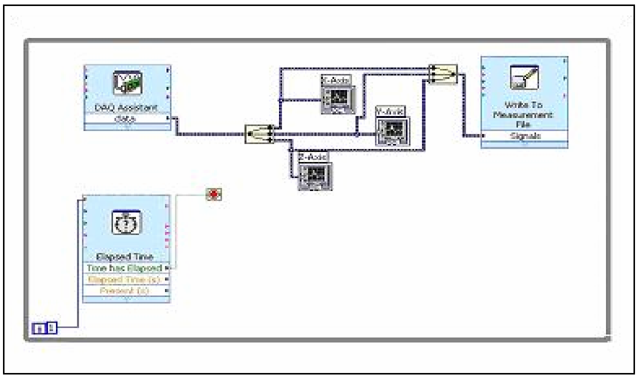

Figure-4. Block diagram of lab view program.

7. RESULTS AND ANALYSIS

The cutting conditions were as given in the table.

Conditions	I	II
Speed	510 rpm	830rpm
Depth of cut	0.5 mm	0.75 mm
Feed	60mm/min	60mm/min

The time series plots of acceleration for the conditions I and II at entry, middle and exit of the workpiece were obtained. The acquired time series data are further analysed using VRA software to generate RPs. The procedure followed to get RP and RQA values are:

a) Average Mutual Information analysis was performed to get embedded time delay value.
b) False Nearest Neighbour analysis is carried out to determine embedded dimension.
c) Recurrence plot was generated using the available values of embedded time delay and dimension.
d) RQA analysis was carried out using time delay, dimension and threshold radius, which was set as 20% of maximum Euclidean distances of acceleration vectors. Epoch study of data was considered, where in 5000 data samples were selected at each epoch with data shift of 200 samples. Overlapping of data samples was done to consider the influence of previous and succeeding data. A total of 10 numbers of epochs were considered for the study and all RQA parameters were obtained.

Time series graphs for cutting condition I, at entry, middle and exit position of workpiece is shown in Figure-5. Time is considered as number of data samples. On observation not much difference is seen among the 3 states from these graphs.

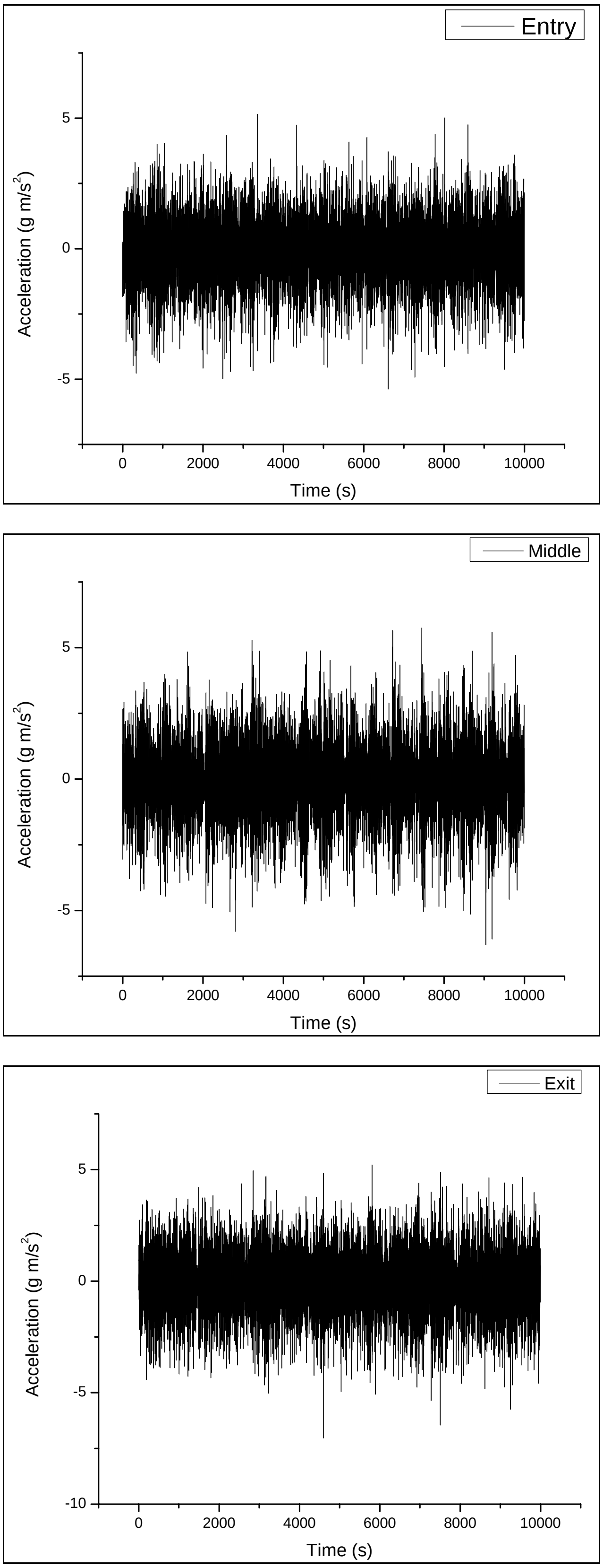

Figure-5. Time series plots of acceleration for condition I at entry, middle and exit.

The time series data on further analysis using AMI and FNN results in embedded parameters, time delay

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of 2 and dimension of 13 are shown in Figure-6 and Figure-7.

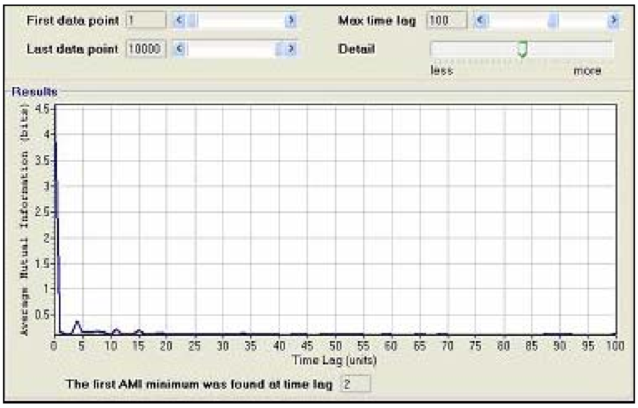

Figure-6. AMI for condition I at middle.

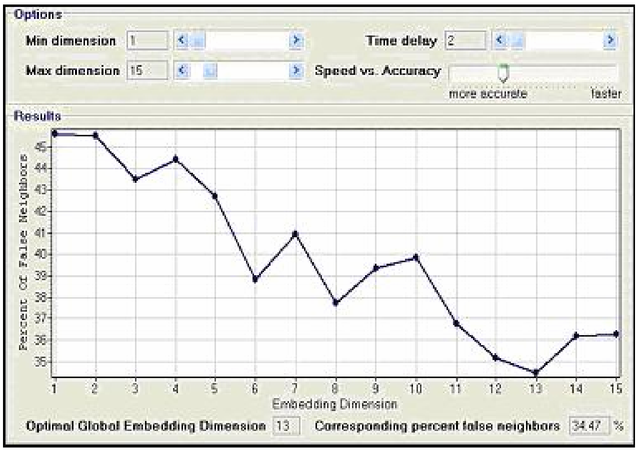

Figure-7. FNN for condition I at middle.

Using the results of AMI and FNN the corresponding recurrence plots were developed without considering threshold radius as shown in Figure-8. A clear distinction in the patterns of RP was observed for cutting at entry, middle and exit.

Information about the dynamics of a time series is usually obtained from the line structure and point density in a RP. A homogeneous RP with no structure is typical of a stationary or autonomous process such as white noise. RPs of oscillating systems, on the other hand, has diagonally oriented or periodic recurrent structures (i.e., diagonal lines or checkerboard patterns). Vertical or horizontal lines in a RP signify the presence of laminarity or intermittency in the time series, whereas abrupt changes in dynamics as well as extreme events are characterized by white areas or bands [31]. As seen in Figure-6 it is found that there are several vertical lines identifying the presence of intermittency in the acceleration time series at the entry. The RP has a checkerboard structure suggesting a regular oscillatory behavior at the middle. The checkerboard structure diminishes showing intermittency as cutter exits from workpiece. The texture provides the first hand information of the underlying dynamics of the system. It provides a qualitative view. RQA analysis supports the distinction by quantifying the results.

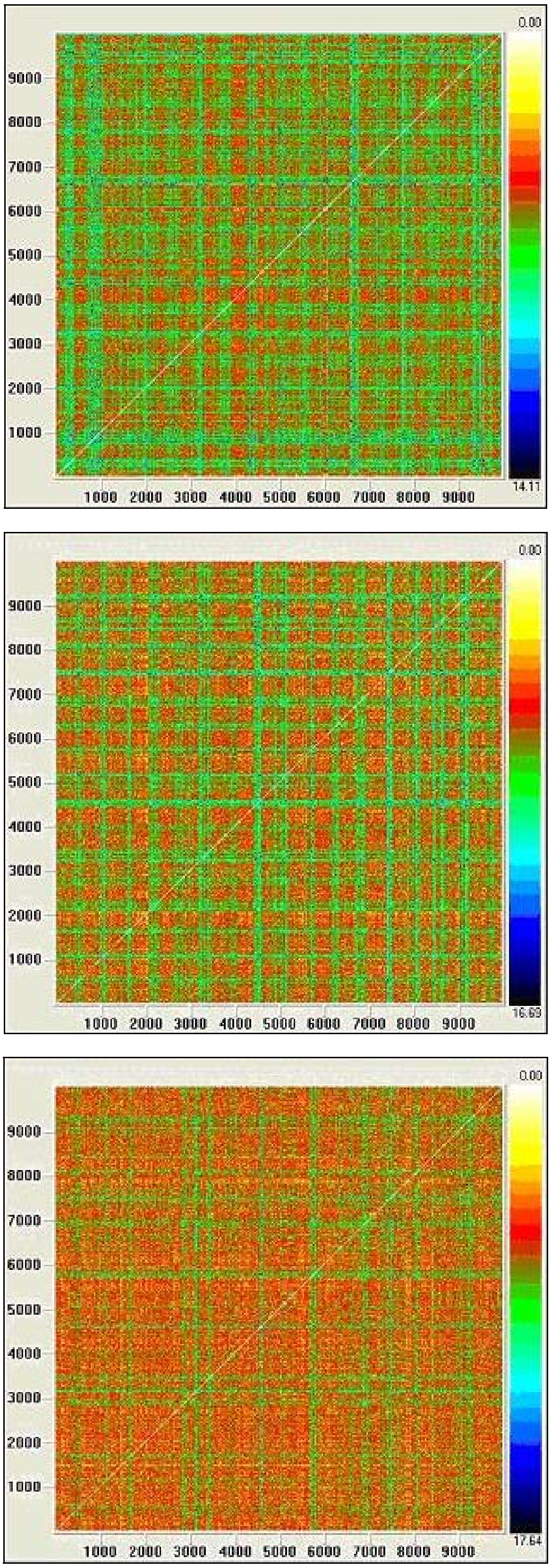

Figure-8. Recurrence plots for condition I at entry, middle and exit.

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RQA analysis

The RQA analysis for the two cutting conditions are tabulated for entry, middle and exit conditions as illustrated in Tables 1 to 6, considering 10 epochs. Only Percent recurrence RR, Percent determinism DET, Percent Laminarity LAM and Trapping Time TT are considered during analysis for reason of simplicity. These parameters show peculiar trends during transient cutting and steady state cutting phases for two different cutting conditions.

From Tables 1 to 3, the REC values changes from 3 to 4 at entry, 7 to 8 at middle and 14 to 15 at exit. It shows an increasing trend which makes the distinction between entry, exit and steady state of cutting. Similar increasing trend is seen in DET parameter. This is observed for condition I.

Table-1. RQA analysis for condition I at entry.

Entry	**d=2**	**n=13**	**ε =3.525**	
EPOCHS	REC	DET	LAM	TT
1	4.06	17.96	19.45	2.80
2	3.36	17.61	18.69	2.77
3	3.93	17.72	18.68	2.75
4	3.80	17.50	19.32	2.79
5	3.99	17.74	19.43	2.78
6	4.34	18.63	20.38	2.77
7	4.33	18.94	20.44	2.83
8	4.21	18.30	19.79	2.77
9	4.42	19.29	22.35	2.94
10	4.17	19.49	22.65	2.98

Table-2. RQA analysis for condition I at middle.

Middle	**d=2**	**n=13**	**ε =4.175**	
EPOCHS	REC	DET	LAM	TT
1	8.52	31.04	36.78	3.43
2	7.93	30.50	35.94	3.45
3	7.98	29.75	36.06	3.32
4	8.65	31.65	38.88	3.64
5	7.89	31 .29	38.08	3.65
6	7.96	30.86	37.53	3.55
7	8.36	31.83	38.85	3.56
8	7.67	31.58	37.66	3.54
9	8.09	32.04	37.80	3.49
10	8.00	32.30	38.43	3.55

Table-3. RQA analysis for condition I at exit.

Exit	**d=2**	**n=11**	**ε =4.41**	
EPOCHS	REC	DET	LAM	TT
1	14.14	33.56	36.01	3.04
2	13.71	33.08	34.72	2.98
3	13.89	33.63	34.62	2.99
4	14.66	34.08	35.43	3.01
5	14.23	34.89	34.49	3.02
6	14.20	34.69	34.39	3.01
7	14.73	36.10	36.53	3.13
8	15.00	37.17	37.45	3.15
9	14.67	35.19	35.21	2.96
10	14.67	34.95	34.19	2.96

As condition changes to II the decreasing trend is seen in REC and DET values as observed from Table-4 to Table-5 the other RQA parameters do not show significant trend .

Table-4. RQA analysis for condition II at entry.

Entry	**d=2**	**n=5**	**ε =5.83**	
EPOCHS	REC	DET	LAM	TT
1	23.76	53.61	39.11	3.3
2	23.49	53.03	38.37	3.33
3	24.17	53.30	33.22	3.33
4	24.12	63.57	38.75	3.36
5	23.87	63.40	38.39	3.37
6	23.65	52 .81	38.00	3.36
7	23.70	52.55	38.37	3.35
8	23.59	52.51	38.37	3.34
9	23.12	52.21	37.00	3.29
10	23.11	51.98	37.88	3.30

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Table-5. RQA analysis for condition II at middle.

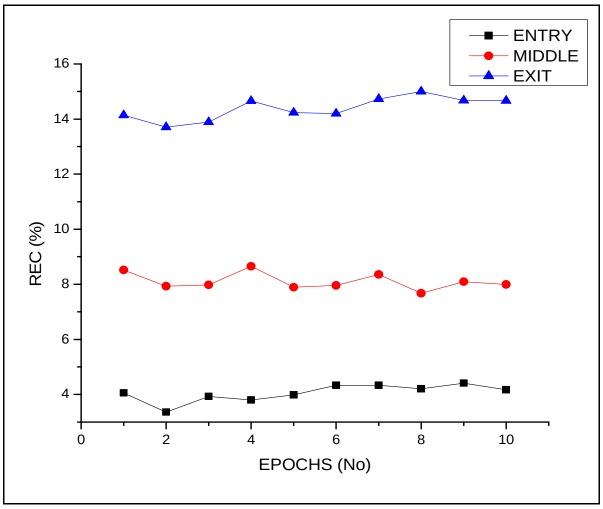
Middle	d=2	n=7	ε =7.395	
EPOCHS	REC	DET	LAM	TT
1	22.62	48.89	39.85	3.55
2	22.77	48.97	39.45	3.56
3	22.82	49.23	39.72	3.59
4	22.35	43.49	39.00	3.54
5	22.45	48.22	37.99	3.49
6	22.73	48.17	39.00	3.50
7	22.85	48.18	39.00	3.51
8	22.51	47. 84	36.00	3.46
9	22.58	48.29	38.57	3.48
10	22.43	48.57	37.00	3.47

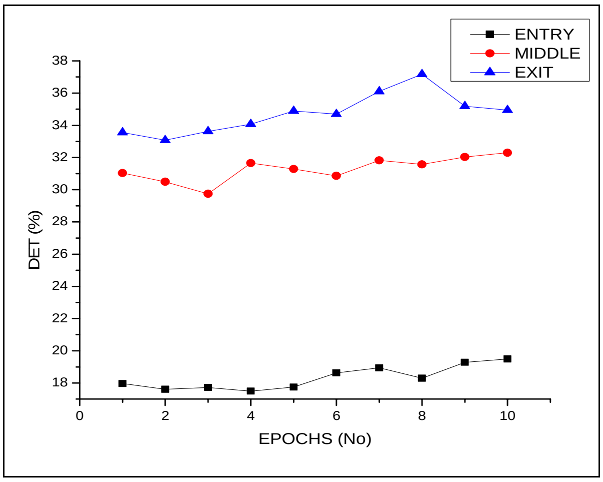
Table-6. RQA analysis for condition II at exit.

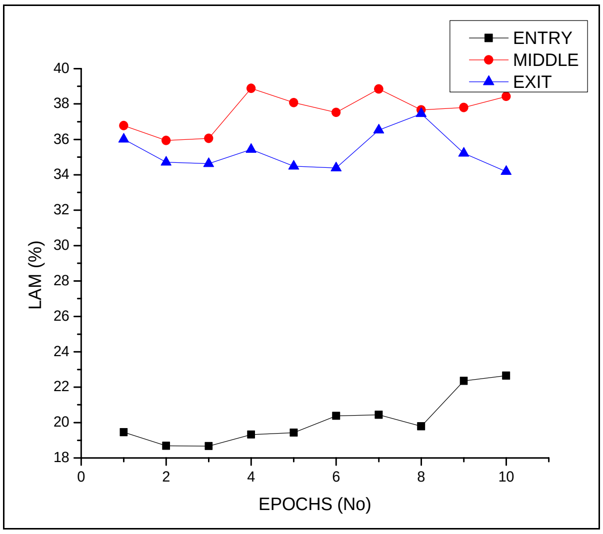
Exit	d=2	n=14	ε =8.61	
EPOCHS	REC	DET	LAM	TT
1	2.79	20.61	8.50	2.57
2	2.82	20.76	8.58	2.57
3	2.88	20.22	8.58	2.56
4	2.96	20.13	8.59	2.55
5	2.99	19.67	8.32	2.56
6	3.25	19.74	10.07	2.61
7	3.40	19.86	10.89	2.67
8	3.50	20.26	12.19	2.65
9	3.60	20.26	12.54	2.66
10	3.55	20.04	12.49	2.65

The RQA parameter versus epoch No plots obtained from tabulated results are shown for the conditions I and II in Figure-9 and Figure-10 respectively. The graphs for condition I and condition II differ due to different cutting condition of speed, feed rate and depth of cut. The epoch study significantly reveal whether cutting is taking place at entry, exit or at middle of workpiece in both of the cases.

Condition I







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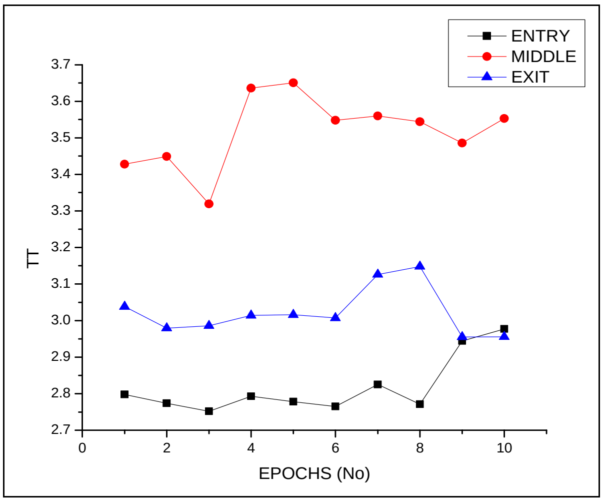
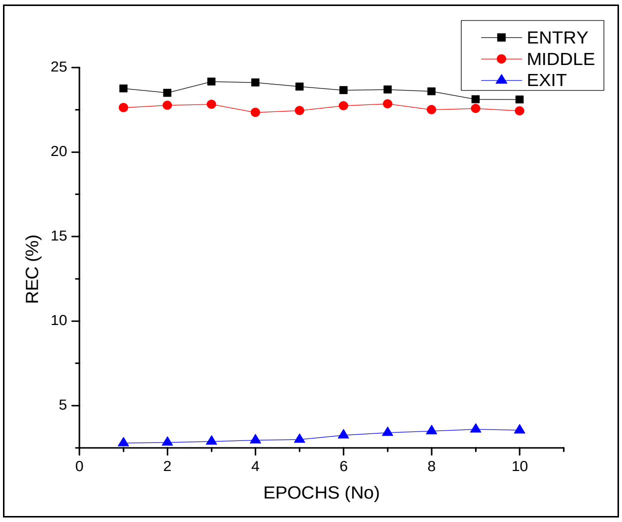
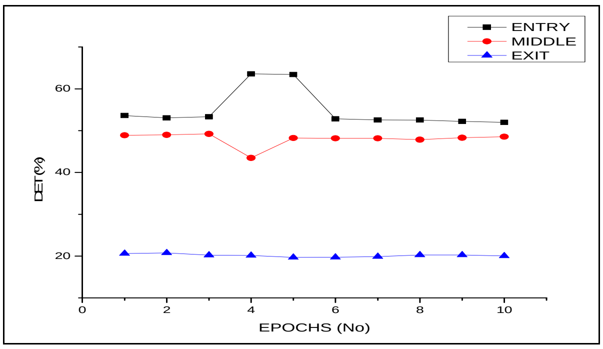
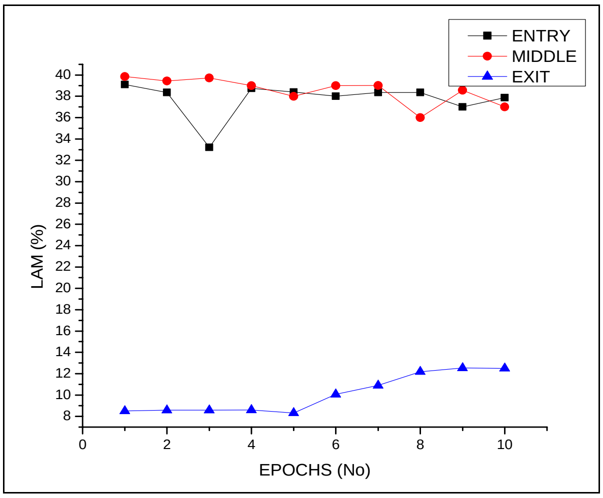


Figure-9. RQA parameter plots for entry, middle and exit positions for condition I.

Condition II







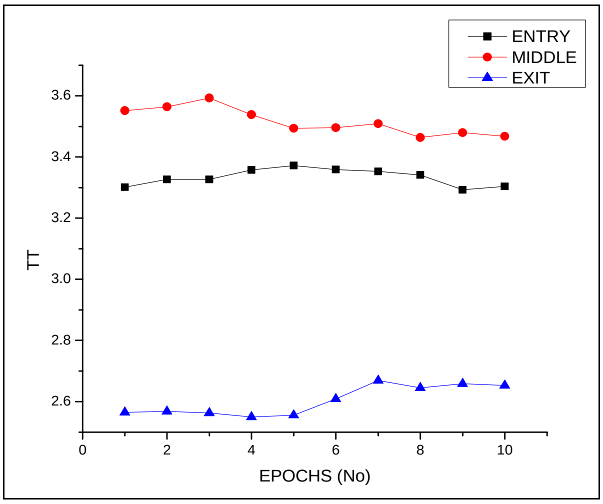


Figure-10. RQA parameter plots for entry, middle and exit positions for condition II.

8. CONCLUSIONS

RP plots were able to clearly distinguish between cutting at entry, middle and exit of the workpiece by its difference in the patterns. The texture differences in the plots are the indicators of the different cutting stages. This provided a qualitative approach to the analysis. A quantitative analysis using RQA parameters well corroborated in bringing out the differences of cutting states.

It is found that percentage recurrence, percentage determinism and trapping time gives clear distinction between cutting at entry, exit and steady cutting as seen for condition I and condition II.

Percent Laminarity gave clear distinction between the three states especially for condition I whereas for condition II the exit condition was more prominently distinct from other states.

Entry state exhibited lower values of REC, DET, TT and LAM for condition I, whereas for condition II, the exit state exhibited lower values of REC, DET, TT and LAM. This was due to change in speed and depth of cut.

Speed was increased from 510 rpm to 830 rpm and depth of cut was increased from 0.5 mm to 0.75 mm.

Identification of entry, exit and steady state cutting is important as it is first prior step before predicting tool wear, tool chatter and tool breakage from cutting tool vibration signals. It will avoid false prediction and assist in developing efficient automated tool condition monitoring. This technique of identifying transient and steady state cutting using RQA parameters synergized with other technique will assist in better process planning and also in optimizing tool geometry.

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