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DRIVE MOTOR CURRENT SENSOR BASED TOOL FLANK WEAR MONITORING USING CHAOS THEORY

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ABSTRACT
This study reports the results of nonlinear time series analysis applied to the captured lathe drive motor current sensor signals for the purpose of identifying various degrees of flank wear on lathe tool inserts. The results show that the chaos analysis carried out on the signals is capable of classifying the intended tool conditions during turning – fresh, semi worn and fully worn – utilizing the single value correlation dimension index extracted from the reconstructed chaotic attractor, assuming constancy of the underlying system parameters. This paper presents the experimental results and shows that drive motor current signals can transmit tool wear conditions reliably.

Key words: Tool condition monitoring, tool wear, time series analysis, Correlation Dimension

1. INTRODUCTION

Tool condition monitoring (TCM) is one of the determining factors for the efficient operation of any machining process where the cutting tool is subjected to continuous wear due to its intermittent or constant contact with the work piece material. TCMs are needed to ensure better quality of jobs and to get reduction in the downtime of machine tools due to catastrophic tool failures, resulting in significant cost savings for manufacturers on account of increased productivity and process reliability. The development of a TCM is divided into the sensor selection, feature extraction from generated signals and, finally, classification of the processed information so as to determine the tool wear. The success rate of a robust and feasible tool condition monitoring system depends on the development of an appropriate signal processing technique in order to maximize the information utilization of the captured sensor signals. In this work the techniques of chaotic time series analysis are applied as an attempt to characterize the measured current sensor signal and the corresponding phenomena by the time-invariant characteristic; correlation dimension, which help to arrive at a reliable conclusion of the tool condition.

Most often, in signal analysis, the amplitude distribution of the signal is analyzed and various statistical moments, like mean value, deviation, skewness and kurtosis are used as characteristics. To gain information about dynamic properties, time varying sensor signals are treated as time series and characterized in frequency space by a power spectrum. Amplitudes of dominant spectral peaks are typically used as characteristics. Dominant peaks at certain frequencies in the power spectrum are typical for periodic and quasi-periodic signals, while measurement noise adds a broadband floor to the spectrum [1]. It was shown by Kantz et al.[2] that the broadband floor in the spectrum could result either from external additive noise or from the inherent properties of a nonlinear deterministic process. To characterize the source of complexity, which is reflected as broadband spectrum, the methods of non-linear time series analysis were introduced by the theory of chaos[2]. To apply these methods the dynamics are presented in a phase space . When the equations that govern process dynamics are not known, the phase space can be reconstructed from a measured time series by using only one observation [3]. The equivalent phase space trajectory preserves the topological structures of the original phase space trajectory, Due to this dynamical and topological equivalence, the characterization and prediction based on the reconstructed state space is as valid as if it was made in the true state space. The attractor so reconstructed can be characterized by a set of static and dynamic characteristics. The static characteristics describe the geometrical properties of the attractor whereas the dynamical characteristics describe the dynamical properties of nearby trajectories in phase space. It has been shown by Govekar [4] that, generally, the most appropriate characteristic in condition monitoring etc. are the static characteristics. Among them the most frequently applied characteristic is the correlation dimension. Bukkapatnam et. al [5] have clearly established that machining dynamics exhibits low dimensional chaos under normal operating conditions. Since dimension estimation relies on the structural information regarding the chaotic attractor of machining dynamics, it was found to be more robust compared with those developed using the statistical signal properties alone [6]. The feasibility of using the correlation dimension as a useful feature extracted from the captured current sensor signals in tool condition monitoring of a lathe is investigated here.

2. EXPERIMENTAL SETUP AND DATA ACQUISITION

Experiments were conducted on a 3.7kW, 1400-rpm PSG heavy-duty lathe using CNMG 120408 PM carbide inserts with standard tool holder. The work pieces were made of 30ϕ x 300mm mild steel. Three sets of experiments using three different quality tools; fresh tool, partially worn and worn tool, with four trials in each set were conducted. A total of 12 sets of experiments were conducted. In the experiment, a fresh tool is characterized by flank wear=0mm, a partially worn tool has a flank wear=0.15mm whereas a worn tool has a flank wear =0.3mm. The cutting factors; speed (560 rpm), feed per revolution (0.06mm) and depth of cut (0.2mm) were maintained constant.

The current sensors are cheap, reliable and can be measured easily and can be kept away from the machining area and therefore less susceptible to harsh cutting conditions. The data acquisition system therefore uses a line current sensor to measure the current drawn by the lathe drive motor. The sensor used consists of a current transformer (CT) having an output range of ±5 volts. The analog voltage signal from the output of the CT is sent to DAC NI PCI 6221 using NI SHC68-68-EPM and SCB 68 for converting it to the digital domain. The sampling rate is fixed at 500Hz. The digitized data is recorded in the PC hard drive using NI LabVIEW.

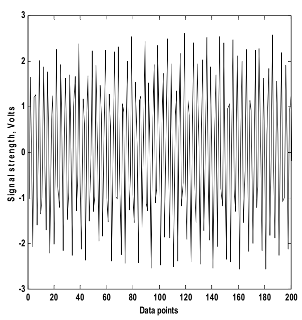

Fig. 2 (a). Fresh tool

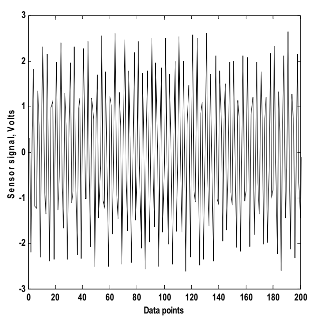

Fig.2 (b). Partially worn tool

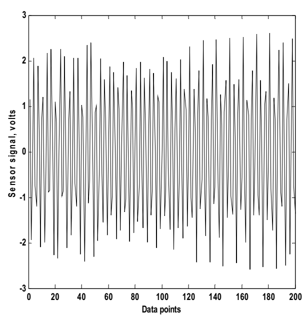

Fig.2 (c) Fully worn tool

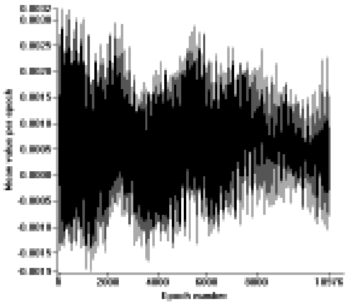

Fig. 3 (a). Fresh tool

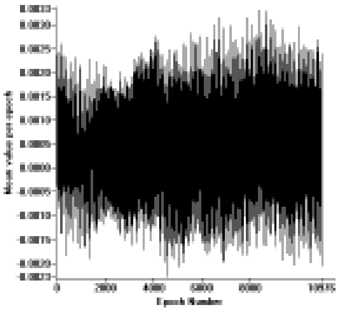

Fig.3 (b). Partially worn tool

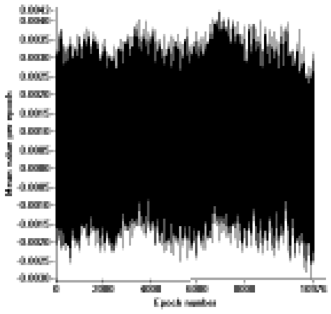

Fig. 3 (c) Fully worn tool

3. ANALYSIS OF DATA

The data length is chosen to be 12000. Fig. 2 (a), (b) and (c) are time series plots of the sensor signals sampled at the designed frequency

3.1 NON LINEAR TIME SERIES ANALYSIS

The finding of Bukkapatnam et. al [5] that machining dynamics exhibits low dimensional chaos under normal operating conditions evidences a deterministic dynamic origin of data. This has necessitated nonlinear analysis of the data. The basic concept in nonlinear data analysis is the analysis of phase space since the time evolution of the phase space trajectory explains the dynamics of the system, i.e. the attractor of the system.

3.1.1 NON- STATIONARITY

Almost all methods and results on time series analysis assume the validity of the conditions that the parameters of the system under study remains constant and that the phenomenon is sufficiently sampled. The requirement of stationarity is a consequence of the fact that we try to approach a dynamical phenomenon through a single time series, and hence is a requirement of almost all statistical tools for time series data, including the linear ones [2]. Stability can be assured in a simulation, but in an experiment it is far from certain. Hence the question becomes whether or not parameter drift or non-stationarity is significant [7]. A statistical test was performed that would identify strong drifts in the data. A sliding window of length 1024 points was applied to the data sets. Successive values of the average of each overlapping moving window are computed throughout the entire data set of 12000 points with single data point shift. Results of the drift in mean value are shown in Fig. 3 (a), (b) and (c). for the different tools. It can be seen from the plots that the mean value undergoes a fluctuating trend that does not appear to be random. This fluctuation is not very significant in relation to the full extent of the data. The fluctuation in the mean is less than 1%, so it was ignored.

3.1.2. PHASE SPACE RECONSTRUCTION.

Delay coordinate reconstruction is the standard first step in most non-linear time series analysis algorithms and proceeds by forming the multidimensional state space trajectory of the signal. Takens [3] proved a theorem that is the firm basis of the methodology of delays. Since one variable only is measured (the usual case in an experiment) the delay coordinate approach is used in the present analysis. Given a time series $x(1), x(2), x(3), ...x(N)$ we define points $X(i)$ in an m-dimensional state space as

$$X(i) = [x(i),\ x(i+\tau),\ x(i+2\tau), ...x(i+(m-1)\tau)] \quad (1)$$

for $i = 1,2,3,....,N-(m-1)\tau$ where i *are* time indices, τ, a time lag and m is called the embedding dimension. Time evolution of $X(i)$ is called a trajectory of the system, and the space, which this trajectory evolves in, is called the phase space. The parameter τ plays an important role in proper reconstruction of phase space and need to be carefully chosen. After the transients are over, the evolution of the trajectory of the system settles typically near a subset of an m-dimensional space and is called an attractor [8].

3.1.2.1 SELECTING THE MINIMUM EMBEDDING DIMENSION

The purpose of the time-delay embedding is to unfold the trajectory in a sufficiently large state space. If the embedding dimension is too low, some neighbor points may be close to each other due to the projection from some higher dimension down to their lower dimension. Whereas, too high an embedding dimension can lead to excessive computation during evaluation of parameters. As Franca and Savi [9] indicates, the method of false nearest neighbors is insensitive to noise; it is utilized here for the determination of the embedding dimension.

By checking the neighborhood of points embedded in projection manifolds of increasing dimension, the algorithm eliminates 'false neighbors'. This means that points apparently lying close together due to projection are separated in higher embedding dimensions [10]. A natural criterion for catching embedding errors is that the increase in distance between two neighbored points is large when going from dimension *m* to *m+1*. This criterion is stated by designating as a false nearest neighbor any neighbor for which the following is valid.

$$\left[\frac{R_{m+1}^2(i,r)-R_m^2(i,r)}{R_m^2(i,r)}\right]^{1/2}=\frac{|x(i+m\tau)-x(i_r+m\tau)|}{R_m(i,r)}>R_{tol} \tag{2}$$

Here i and i_r are the times corresponding to the neighbor and the reference point, respectively. R_m denotes the distance in phase space with embedding dimension m and R_{tol} is the tolerance threshold. Fig. 4 shows that the percentage of false nearest neighbors drops to a lower value when the embedding dimension is increased. For the analysis the embedding dimension corresponding to the lowest value of FNN is selected.

3.1.2.2 SELECTING THE TIME LAG

To choose the time lag, τ, we use the non linear correlation function of average mutual information, which, again as Franca and Savi [11] indicates, has no noise sensitivity. Fraser et. al [12] establishes that delay corresponds to the first local minimum of the average mutual information function $I(\tau)$ which is defined as follows.

$$I(\tau)=\sum P(x(i),x(i+\tau))\log_2\left[\frac{P(x(i),x(i+\tau))}{P(x(i))P(x(i+\tau))}\right] \tag{3}$$

where $P(x(i))$, is the probability of the measure $x(i)$, $P(x(i+\tau))$ is the probability of the measure $x(i+\tau)$ and $P(x(i),x(i+\tau))$ is the joint probability of the measure of $x(i)$ and $x(i+\tau)$. Plotting $I(\tau)$ versus τ makes it possible to identify the best value for the time delay, which is related to the first local minimum (Fig. 5).

Table 1 shows the parameter values used in the phase space reconstruction for the different quality tools used. The time lag value is located at the first local minimum of the average mutual information function and the embedding dimension by false nearest neighbors algorithm.

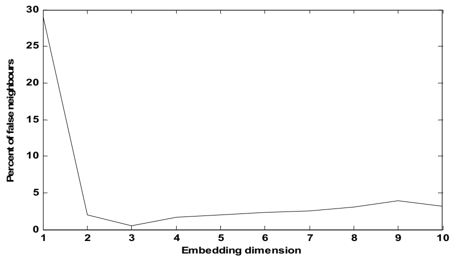

Fig. 4 False Nearest Neighbors- Fresh tool

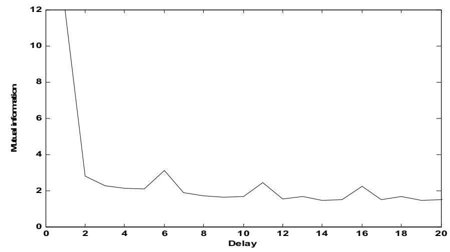

Fig. 5 Average mutual information - Fresh tool

Tool condition	Time lag, τ	Embedding Dimension m
Fresh	3	3
Partially Worn	3	5
Fully Worn	3	5

Table 1 Phase space reconstruction parameters

After the embedding parameters have been determined, the attractor of the processes are reconstructed in the phase space as in Fig. 6(a), (b) and (c). The phase space presents a chaotic like characteristic because the orbit is not a closed curve.

3.1.3 ATTRACTOR DIMENSION

Attractors associated with chaotic dynamics have a fractional dimension. Since fractal dimension has to do only with the geometrical structure of the attractor a more relevant measure; the correlation dimension is used for characterizing the attractor. Correlation dimension as proposed by Grassberger et al [13] is calculated using the distances between each pair of points in the set of N number of points as $s(i,j)=|x_i - x_j|$, Here r is the radius of sphere we place at each point on the orbit for calculating the distance [14]. The correlation function , $C(r)$ is now defined as

$$C(r) = \lim_{N\to\infty} \frac{1}{N^2} \sum_{j=1}^{N} \sum_{i=j+1}^{N} G(r - |x_i - x_j|) \tag{4}$$

where G is the Heaviside function. The Correlation Dimension D_2 is then found as

$$D_2 = \lim_{r\to 0} \frac{\log(C(r))}{\log(r)} \tag{5}$$

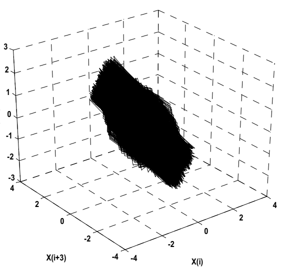

Fig. 6 (a). Fresh tool

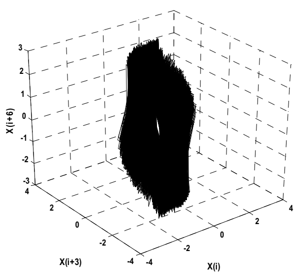

Fig.6 (b). Partially worn tool

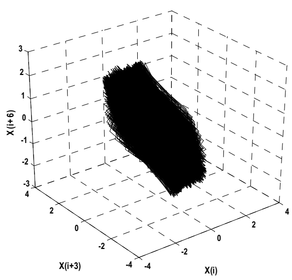

Fig. 6 (c) Fully worn tool

The correlation dimension for different values of embedding dimension for different conditions of tools is presented in Fig.7. The correlation dimension, D_2, reaches a plateau for a range of large enough m values. This plateaued value of D_2 is taken as a true estimate of the correlation dimension of the underlying chaotic attractor [15]. Here, D_2 of the fresh tool is seen below that of the fully worn tool while that of partially worn tool lies almost lying in between. It is suggestive of a distinct response of the correlation dimension towards tool wear.

4. CONCLUSION

The work demonstrates the dependence of the reconstructed attractor dimension on tool condition with respect to flank wear. As the flank wear increases the correlation dimension also must change due to change in cutting dynamics. Here it is established that as the tool wear increases the dimension gets inflated. The analysis thus shows that the D_2 feature extracted from the drive motor current sensor signals can transmit tool wear conditions reliably and can therefore be utilized effectively in tool condition monitoring in lathe. Moreover, the nature of the hardware used makes the system less expensive, reliable and robust.

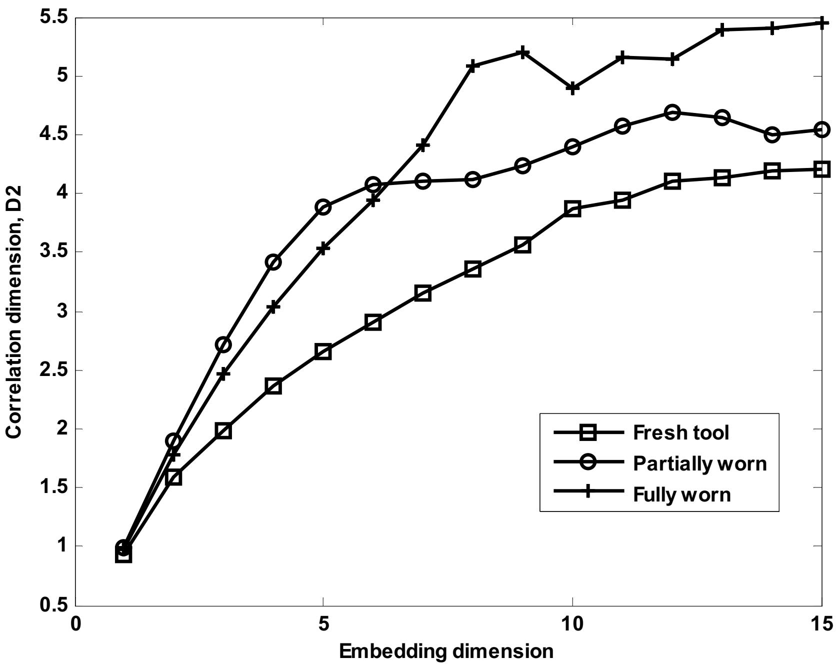

Fig. 7 Finding correlation dimension, D_2, of the three tools studied

Tool types studied	D_2
Fresh tool	4.19
Partially worn tool	4.5
Fully worn tool	5.41

Table 2. , D_2 values of the three tools studied

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