PERMUTATION ENTROPY BASED ANALYSIS OF COMPLEX SIGNALS FOR CHARACTERISING CHANGE IN SYSTEM DYNAMICS

A Thesis

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DOCTOR OF PHILOSOPHY

by

USHA NAIR

DIVISION OF MECHANICAL ENGINEERING, SCHOOL OF ENGINEERING
COCHIN UNIVERSITY OF SCIENCE AND TECHNOLOGY, KERALA
INDIA

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DECLARATION

I hereby declare that the work presented in this thesis entitled "Permutation Entropy Based Analysis of Complex Signals for Characterising Change in System Dynamics" is based on the original work done by me under the supervision and guidance of Dr. Narayanan Namboothiri V.N., Faculty Division Of Mechanical Engineering, School of Engineering, and co guidance of Prof. V.P. Narayanan Nampoori, International School of Photonics, Cochin University of Science and Technology. No part of this thesis has been presented for any other degree from any other institution.

Usha Nair

Thrikkakara

19-12-2008

CERTIFICATE

This is to certify that the thesis entitled "Permutation Entropy Based Analysis of Complex Signals for Characterising Change in System Dynamics" is a report of the original work done by Usha Nair under my supervision and guidance in the School of Engineering, Cochin University of Science and Technology. No part of this thesis has been presented for any other degree from any other institution.

Dr. Narayanan Namboothiri V.N.
Supervising Guide,
Division Of Mechanical Engineering,
School of Engineering

Prof. V.P.N. Narayanan Nampoori
Co-Guide,
International School of Photonics,

Cochin University of Science and Technology

Thrikkakara

19-12-2008

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ABSTRACT

Timely detection of sudden change in dynamics that adversely affect the performance of systems and quality of products has great scientific relevance. This work focuses on effective detection of dynamical changes of real time signals from mechanical as well as biological systems using a fast and robust technique of permutation entropy (PE). The results are used in detecting chatter onset in machine turning and identifying vocal disorders from speech signal.

Permutation Entropy is a nonlinear complexity measure which can efficiently distinguish regular and complex nature of any signal and extract information about the change in dynamics of the process by indicating sudden change in its value. Here we propose the use of permutation entropy (PE), to detect the dynamical changes in two non linear processes, turning under mechanical system and speech under biological system.

Effectiveness of PE in detecting the change in dynamics in turning process from the time series generated with samples of audio and current signals is studied. Experiments are carried out on a lathe machine for sudden increase in depth of cut and continuous increase in depth of cut on mild steel work pieces keeping the

speed and feed rate constant. The results are applied to detect chatter onset in machining. These results are verified using frequency spectra of the signals and the non linear measure, normalized coarse-grained information rate (NCIR).

PE analysis is carried out to investigate the variation in surface texture caused by chatter on the machined work piece. Statistical parameter from the optical grey level intensity histogram of laser speckle pattern recorded using a charge coupled device (CCD) camera is used to generate the time series required for PE analysis. Standard optical roughness parameter is used to confirm the results.

Application of PE in identifying the vocal disorders is studied from speech signal recorded using microphone. Here analysis is carried out using speech signals of subjects with different pathological conditions and normal subjects, and the results are used for identifying vocal disorders. Standard linear technique of FFT is used to substantiate the results.

The results of PE analysis in all three cases clearly indicate that this complexity measure is sensitive to change in regularity of a signal and hence can suitably be used for detection of dynamical changes in real world systems. This work establishes the application of the simple, inexpensive and fast algorithm of PE for the benefit of advanced manufacturing process as well as clinical diagnosis in vocal disorders.

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ABBREVIATIONS

LE	Lyapunov Exponent
K-S entropy	Kolmogorov-Sinai entropy
FNN	False Nearest Neighbour
RMS	Root Mean Square
AE	Acoustic Emission
FFT	Fast Fourier Transform
CER	Course –grained Entropy Rate
CIR	Course –grained Information Rate
NCIR	Normalised Course –grained Information Rate
CT	Current Transformer
CCD	Charge Coupled Device
PE	Permutation Entropy
ApEn	Approximate Entropy
SampEn	Sample Entropy
MSE	Multi Scale Entropy
R	Optical roughness parameter

CHAPTER 1-INTRODUCTION

Physical systems are inherently nonlinear and exhibit aperiodic, strange and irregular behaviour. Linear models of these processes do not capture several critical and strange behaviours encountered in real time basis. Characterisation of irregular broad band signal of nonlinear dynamical systems and the extraction of useful information provide significant insight in to the type of behaviour shown by the system. Some sudden and dramatic change in nonlinear systems may give rise to the complex behavior called chaos. Under certain conditions their behaviour becomes aperiodic with random like appearance. With the emergence of nonlinear dynamical analysis many researchers have striven to find out the nonlinear behaviour of various systems with practical applications. During the last few decades several investigations have been carried out in the manufacturing and medical field from the nonlinear point of view. Analysis of real world phenomena using methods from nonlinear dynamics is based on the state space to describe the state and behavior of a system. The phase space is built from dynamical variables necessary to determine the state of a nonlinear system. The dynamics of a system with many degrees of freedom can be investigated using time series of a single scalar observable output state. The complex behaviour can be interpreted as manifestations of strange attractors in state space. Various invariant measures that show the nonlinear behavior of systems are developed during the past few years. Two areas in which the nonlinear approach with fast and robust technique of characterization, monitoring and control is essential are machining process under mechanical systems and biological signals in medical science.

Machining is the fundamental manufacturing process in production industry. Ultra precision machining and high speed machining are the two major challenges with great scientific relevance in this field. One of the most important factors that decide the performance and efficiency of the machining process, quality and dimensional accuracy of the product is the chatter phenomenon resulting from the excessive vibration between the tool and work piece. Recent developments in advanced manufacturing and automation in processing industry demands very fast chatter detection and avoidance mechanisms. Linear methods of chatter identification and control depend on the assumption that the system dynamics is time invariant. However, it is well established that cutting dynamics is nonlinear and exhibits low dimensional chaos. This enhances the need for nonlinear approach towards the identification and control of chatter for improving the machining efficiency and better quality of the product.

Chaos based measures are formulated under the assumption that the signal is stationary and originates from low dimensional nonlinear system. The effectiveness of applying the existing methods to time varying and noise contaminated signal has limitations in producing reliable results. Moreover most of these methods are computationally expensive and hence efficient algorithms must be used to speed up calculation for online analysis of real time signals.

With recent advances in nonlinear studies, its application in biological signals has sparked great interest among researchers. Motivated by the evidences of nonlinearity in speech signal, various attempts are made towards more detailed characterization of complexity and strangeness in phoneme attractors. But due to the nonstationary nature of the speech signal the application of any tool derived from the concept of deterministic chaos appears to be meaningless. Furthermore when dealing with vocal pathologies the situation becomes more complex as it is not obvious how one could quantify the entity of the disease. Different linear as well as nonlinear methods of characterization and modeling are based on the quasi deterministic nature of the voice signal. However the success of all methods depends upon the presence of noise content in the signal. Ordinary noise reduction technique based on decomposition of contaminated signal into original signal and random fluctuations fail in the cases of abnormalities in speech signal. This is because the undesirable part of the signal is also highly correlated to the clean part of the signal and cannot be treated as pure noise. In such cases separation into signal and noise fails for most part of the frequency domain. To deal with such situations it is essential to have fast and robust techniques capable of producing reliable results from real time signals. The new concept of permutation entropy addresses these problems to a great extent.

Permutation entropy provides useful information about the change in dynamics of regular, noisy or chaotic data. As this measure is robust against dynamical as well as observational noise it is considered as an effective tool in real time chatter detection in industrial environment. This work, therefore, employs PE methodology for the analysis of sensor signals and investigates the effectiveness of PE in the detection of chatter onset in turning process and identification of vocal disorder in speech signal.

1.1 MOTIVATION

Most of the real time processes deal with signals with huge data sets contaminated with dynamical and observational noise. There are situations which demand almost instantaneous analysis of such signals so as to implement corrective measures in time before the system gets damaged. Therefore the applicability of any real world data analysis method depends highly on the data processing time. Most of the existing methods of signal analysis 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 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.

1.2 AIM OF THE THESIS

In order to explore the important and valuable information hidden in the nonlinear dynamical system from noise contaminated sensor signals, the present nonlinear approach becomes insufficient as the results are sensitive to signal to noise ratio. Also, attention is to be paid when dealing with nonstationary signals of various practical importances.

Our goal is primarily to detect dynamical changes using a fast, robust and low cost technique from large real world data sets where there is no time for preprocessing and fine tuning of data. Here we aim to make use of the versatile and invariant properties of permutation entropy for this purpose by establishing a link with the conventional state space approach. The practical application of PE methodology is its usefulness in detecting dynamical changes in turning process and thereby effective in indicating the onset of chatter. We also aim to study the effectiveness of PE in extracting the change in dynamics caused by abnormalities in the vocal tract. This may be of great advantage in preliminary clinical diagnosis in identifying the vocal disorders before proceeding for further expensive treatment strategy. More precisely, the aim of the thesis are

- To study the nonlinear characteristics of turning in a lathe machine
- To study the nonlinear properties of normal and abnormal speech processes
- To investigate the effectiveness of permutation entropy in detecting change in dynamics in the above processes from different sensor signals acquired
- To investigate the applicability of PE in detecting onset of chatter in turning and vocal disorder in speech process
- To study the effectiveness of PE in indicating the variation of surface finish before and after the occurrence of chatter
- To verify the results using existing methods.

1.3 THESIS OUTLINE

Chapter 1 Introduces the problem and defines the aim of the thesis

Chapter 2 Contains review of background literature on nonlinear signal processing techniques with special emphasis given to chatter detection in turning, surface texture analysis and vocal disorders.

Chapter 3 Contains the research methodology adopted in this thesis and explains the technique of Permutation entropy, its advantages compared to conventional methods applied to nonlinear time series analysis.

Chapter 4 Presents experimental setup and data acquisition system used in the experiments.

Chapter 5 Discusses the results of the analysis of experiments on turning process.

Chapter 6 Discusses the results of the analysis of vocal disorders.

Chapter 7 Contains summary, conclusions and scope for future work.

CHAPTER 2-BACKGROUND LITERATURE REVIEW

This chapter gives an overview of the linear as well as nonlinear signal processing techniques with emphasis on the role of entropy in this field. Thrust is given to various developments in the field of nonlinear time series analysis leading to detection of dynamical changes in two nonlinear processes (a) chatter in metal cutting (b) vocal disorder in speech process. Brief review of techniques for surface texture analysis in metal cutting is also carried out in this chapter.

2.1 CHATTER IN METAL CUTTING

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 dynamic conditions can behave in different ways for different modes of vibration [1-3]. The dynamics of cutting process is influenced by many physical phenomena such as material flaw, deformation and fracture, friction, tool wear, vibration of machine tool etc. Instability of cutting process causes self excited large amplitude vibrations of the tool relative to the work piece and is characterized by a dominant nonlinear feedback mechanism connecting the tool displacement and the exciting force [4-

6]. This phenomenon known as chatter adversely affects the performance and efficiency of the cutting process 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 [3]. In general chatter can be classified as regenerative and non-regenerative. Regenerative chatter occurs due to the undulations on the earlier cut surface and non-regenerative is due to the mode coupling among the existing oscillations [7, 8].

Studies aiming at deeper understanding of the dynamics of metal cutting and chatter were initiated in the 1940-s and 1950s, even though significant research was done by Taylor as early as 1907. Arnold [9], Hahn [10] and Doi and Kato [11] were the first to describe the dynamics of chatter. Tobias and Fishwick [12], Tlusty and Polacek [13], Tobias [2] have explained the chatter mechanism using a comprehensive mathematical analysis. With the advent of high speed machining, the importance of understanding the dynamics of chatter as well as significance of control mechanism gained more relevance Tlusty [14, 15]. Earlier studies on metal cutting and chatter dynamics were based on linear analysis methods Merrit [16], Kegg [17, 18]. Cutting process has been identified as strictly nonlinear in later years [1].Various nonlinear effects on cutting dynamics include tool structure nonlinearities, friction at the tool chip interface, loss of tool –work piece contact, influence of machine drive unit on the cutting flow velocity [19] etc. Mechanical models with nonlinear cutting forces were developed by Grabec [20], Lin and Weng [21], Wiercigroch [22, 23]. Nonlinear approach towards understanding the cutting dynamics established the low dimensional chaotic nature of cutting processes Moon [24], Bukkapatnam [25, 26], Wiercigroch and Cheng [27], Stepan and Kalmer-Nagy [28] ,Minis and Berger [29].

Studies of nonlinear phenomena in machine tool operations involved three different approaches.

(1) Measurement of nonlinear force- displacement behavior of cutting or forming tools.

(2) Model based studies of bifurcation using parameter variation.

(3) Time series analysis of dynamic data for system identification.

Fundamental origins of nonlinear dynamics in material processing involve nonlinear relations between stress and strain, or stress and temperature, or chemical kinetics and solid state reactions in material. Other sources involve nonlinear geometry such as contact forces and tool work-piece separation. Many of the fundamental studies of chatter dynamics are based on the assumption of a steady process. Thus in cutting force measurements, the speed and depth of cut are fixed and the average force is measured as a function of steady machine speed and cutting depth. This method however demands the details of real dynamics of the process as to what happens when the cutting depth decreases instantaneously. Average force measurements often filter out the dynamic nature of the process. Earlier models of dynamics considered force measurements as single valued functions of chip thickness and material flow velocity. Moon proposed a hysteretic force model which is not single valued [30].

Bifurcation methodology looks for dramatic changes in the topology of the dynamic orbits at critical values of control parameters. This method introduced new tools like the Poincare maps which help in identifying the different dynamical regimes present in the cutting dynamics. Thus one can connect experimental results with the corresponding dynamical regimes which further helps in designing suitable control strategies [31,32]. However this approach utilizes very simple models and is not based on fundamental physics. This method looses effectiveness in systems with higher dimension [30].

The time series analysis methods have become popular in recent years to analyse many dynamic physical phenomena from ocean waves, heart beats, lasers and machine tool cutting [33]. These methods are based on the use of a series of digitally sampled data from which an orbit in a pseudo-M-dimensional phase space is generated. One of the fundamental objectives of this method is to place a bound on the dimension of the underlying phase space from where the dynamic data were sampled. This can be done with several statistical methods, including fractal dimension, false nearest neighbours (FNN), Lyapunov exponents, wavelets and several others. However if model based analysis can be criticized for its simplistic models, then nonlinear time series analysis can be criticized for its assumed generality. Although it can be used for a wide variety of applications, it contains no physics. It is dependent on the data alone. Thus the results may be sensitive to signal to noise ratio of the source measurement, signal filtering, time delay of sampling, the number of data points in the sampling and whether the sensor captures the essential dynamics of the process.

Parallel studies in a different line of approach claimed that the vibrations are random noise. One of the fundamental questions regarding the physics of cutting solid materials is the nature and origin of low level vibrations in so called normal or good machining. This is cutting below the chatter threshold. Below this threshold, linear models predict no self excited motion. Yet when cutting tools are instrumented, one can see random–like bursts of oscillations with centre frequency near the tool natural frequency. Work by Johnson [31] has carefully shown that these vibrations are significantly above any noise in a lathe – turning operation. Those observations have been done by several laboratories, and the time series methodology has been used to diagnose the data to determine whether the signals are random or deterministic chaos [6, 24 -26,31-41] . This controversy about the dynamical nature being random or deterministic is still under debate.

Given the evolution of any one of the physical variables of a system, the nonlinear time series analysis technique can provide with deep understanding of the dynamical nature of the system. Thus this method assumes great importance. The special task of nonlinear theory in cutting research include

(i) predicting steady chatter amplitude

(ii) providing understanding of subcritical chatter

(iii) explaining pre-chatter low level chaotic vibrations

(iv) predicting dynamic chip morphology

(v) providing new diagnostic for tool wear

(vi) determining control model for chatter suppression, providing clues to better surface precision and quality

Certainly many or all of these goals were basis of traditional research methodology in machining. But the use of nonlinear theory acknowledges the essential dynamic character of material removal processes that in more classical theories were filtered out. However there is a need to integrate the different methods of research, such as bifurcation theory, cutting force characterisation, and time series analysis before nonlinear dynamic modeling can be useful in practice. An equally important consideration is the selection of sensors in acquiring the signal suitable for analysis of the process.

2.2 SENSORS AND SIGNALS

Extensive research using different sensor signals and various signal processing techniques has been performed on chatter detection. Monitoring of machining process depends heavily on the processing techniques employed. Signals acquired from force sensors [41, 42], accelerometers [43], spindle drive current from current sensors [44], audible sound signal from microphone [45, 46], and acoustic emission [47] 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. Regarding chatter detection, Delio et al. compared different sensors and concluded that monitoring the audio signal using microphone is the ideal compromise among these sensors [48].

(i) Force Sensor

It is known that the cutting force is an important variable for chatter detection [49, 50]. Various kinds of cutting force sensors such as Kistler dynamometers have been developed to measure the cutting force. Though these dynamometers provide accurate measurement of cutting force, it can lead to reduction in stiffness of machine tools resulting in chatter, dimensional error, and lack of over load protection [49-51]. The use of force sensors for shop-floor applications is limited also due to its high cost. Bukkapatnam et al. established the chaotic behaviour of cutting dynamics using force sensors [25] and Grabec et al. used it effectively for characterising and detection of chatter [4,6,35-37].

(ii) Accelerometer

Signals from accelerometers are proposed by Bailey at al. [52] for the purpose of chatter detection. An accelerometer mounted close to the cutting region provides for the calculation of ratio called variance ratio to indicate the presence of chatter. These sensors are subject to alteration of signal due to sensitivity to displacement. It is also very difficult to put accelerometer on rotating parts.

(iii) Current Sensor

Electrical current signals are another option for studies of machining process. Current sensors are a good choice as they meet the necessary requirements such as reliability, durability and low cost. As the sensor is placed away from the cutting zone it is not affected by harsh cutting conditions. Spindle drive current of vertical milling machine are used for detection of chatter [44]. Both simulations and experimental studies were conducted to assess the sensitivity of current signal to slight process instability using the statistical indicator –R value. The results revealed the sensitivity of current signal to variation in machine dynamics. Wu et al. [53] developed a new method for tool condition monitoring that used a combination of wavelet transform and binary time series to analyse the spindle motor current signal. Li and Du [54] proposed a two layer artificial neural network for machining error compensation in which both spindle motor current and feed motor current are used. For linear motors, the feed force is directly related to the motor current because of the lack of gearing mechanisms, which is beneficial in calculating the cutting forces from motor current [55-57].

(iv) Acoustic Emission

AE signals are influenced by the tool vibration especially during chatter. Signals are also used effectively for chatter detection in grinding [58]. Experimental studies based on the calculation of coarse grained information rate (CIR) from normal grinding force and RMS acoustic emission signals reveal the sensitivity of these signals to chatter vibrations. Acoustic emission signals from turning process are effectively used for analysis of chatter dynamics [59].

(v) Microphone

Microphone can effectively be used for chatter detection as the acoustic pressure during machining is proportional to the displacement of the tool [60]. Under stable cutting conditions dominant frequencies are spindle speed and tooth passing frequency. When instability is reached some other frequencies appear [61]. Presence of frequencies other than spindle speed or tooth passing frequency is a method to detect chatter. Unlike other sensors, the use of microphone is simple and does not involve any positioning problem. Audio signals are already in use with commercial software like Harmonizer [62]. As it covers a wide range of frequency, environmental noise can distort the signal. However it does not offer linear response below 100Hz and hence it is not possible to detect frequencies below this value.

2.3 CURRENT TECHNIQUES IN NONLINEAR TIME SERIES ANALYSIS

A set of values that vary randomly with time is the time series of a system, the analysis of which gives an understanding of the underlying dynamics. Traditional methods of time series analysis based on statistical characterisations are extensively used in financial markets, population explosion and meteorological observations.

Most conventional linear time series analysis methods [63, 64] implicitly assume that the data come from a linear dynamical system, perhaps with many degrees of freedom and some added noise. Thus the variation is assumed to be a superposition of sine waves or exponentials that grow or decay in time. Most commonly used linear methods to characterise the system dynamics are autocorrelations, Fourier analysis and power spectrum representation. For stationary data with inherent periodicities, Fourier analysis [65] turned out to be extremely useful and this lead to the development of signal processing era in all experimental datas. Signal processing continued to gain importance with the growth of electronic industry and became extremely useful with the invention of Fast Fourier Transform computer program [66]. Spectral analysis saw another fantastic leap with the introduction of wavelets in the mid 1980s [67]. With the invention of information theory by Shanon and Weaver [68] time series could be understood in terms of symbolic dynamics.

In short linear methods interpret all regular structure in a data set as a dominant frequency, as linear correlations. This means that the intrinsic dynamics of the system are governed by the linear paradigm that small causes lead to small effects. Since linear equations can only lead to exponentially growing or periodically oscillating solutions, all irregular behaviour of the system has to be attributed to some random external input to the system. [69].

Signal processing technique can prove to be effective in time series analysis. Nonlinear time series analysis aims at understanding the dynamics of a system using the time series of a single available variable. Chaos theory says that random inputs are not the only source for irregular output of a system: nonlinear chaotic systems with purely deterministic equations of motion can produce very irregular data. Extensive research conducted on nonlinear dynamical systems over recent years have proved that conventional time domain and frequency domain approaches to real world systems are far from optimal. Time series analysis has become a popular approach to the investigation of dynamical behaviour of systems in experiments and field measurements. Traditional signal processing techniques in the form of power spectral analysis [70] are applied to chaotic time series. Delay coordinate embedding [71, 72] introduced to chaotic time series has become the turning point in the development of time series analysis method. Methods which are usually called nonlinear refer to reconstruction and exploitation of structure in state space. The basis of delay reconstruction is the conversion of a scalar time series in to vectors of the state space with appropriate embedding dimension [73-77]. The evolution of these vectors will represent the state space trajectory of the dynamical system which may be attracted to a subspace called the attractor. Most nonlinear techniques depend on analysis and characterization of the attractor properties to study the underlying dynamics of the system. Several algorithms have been proposed for the computation of characteristic invariant measures of the attractor [69, 73-82]. The correlation dimension D2 [83] is a measure of complexity which yields a lower boundary for the degree of freedom of a signal possesses, and in this sense might be regarded as a measure of complexity of dynamical system. The Lyapunov exponents estimate the mean exponential divergence or convergence of nearby trajectories in state space [84]. For a chaotic system the largest Lyapunov exponent (LE) is positive expressing the sensitiveness of the dynamics to initial conditions. Largest LE gives an estimation of chaos level in the dynamical system. The Kolmogrov entropy [85], which is equal to the sum of all LEs describes the average rate at which the information about the state of a dynamical system is lost with time. Reccurrance plot is a distance plot [86] from the symmetric matrix based on the distance between two adjacent points in state space. Recurrence quantification analysis [87-89] is the complexity measure which gives the statistical description of the parallel line distribution of the recurrence plot. These methods have limitations in producing reliable results from real world data with issues of limited data set size, noise and nonstationarity of the signal.

Complexity measures are a class of statistics to characterize time series generated from dynamical processes. The concept of entropy has widespread applications in fields like physics, mathematics, statistics, economics, computer science, literature, earth sciences, biology and others. The meaning of entropy in a particular field corresponds to the interpretation and application requirement of that field. Based in part on French physicist Sadi Carnotts ground work of the 1820s, the German physicist Rudolph Clausius introduced entropy in 1865 in his work on heat producing engines. The general idea is that it is impossible to direct all of a system's energy into useful work, because some of that energy is not available. Entropy in this original thermodynamic (heat movement) sense is a measure of inaccessible energy. High entropy means that much of a system's energy cannot be used for work. In other words only a small part is available for work. Low entropy means that only a small proportion of the system's energy is unobtainable. A key development in the evolution of the concept of entropy is the introduction of a statistical probability measure for the entropy by the Australian physicist Boltzmann. Later in 1870s, a new way of understanding the concept of entropy sprang up wherein it is identified as a measure of information.

The entropy measures quantify the rate of information generation in a system and are found to have application in charaterising real world data. Entropy has many meanings and interpretations. They include proportion of energy available for doing work, disorder, probability of an event, randomness, surprise and information. The fundamental concept of thermal entropy as the amount of disorder in the system can be generalized to characterise the amount of information stored in more general probability distributions. Probabilities or relative frequencies are the basic data used in calculating entropy or information: high probability implies small information, and vice versa. Shanon defines entropy [68] in terms of discrete random variables X with possible states or outcomes x1 ,x2,.....,xn as $H(x) = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i)$ where p(xi) is the probability of the ith outcome of X. When all states are equally probable, entropy is maximum which implies that the dynamics is totally unpredictable. In contrast for periodic dynamics corresponding to less number of possible states, the predictability is very high leading to very low entropy. For deterministic dynamics systems entropy value lies between these two extremes.

To identify chaos we need entropy rate at the limiting conditions of time increasing towards infinity and box size (phase space compartments) diminishing towards zero. This special case of entropy is called Kolmogorov-Sinai (K-S) entropy. K-S entropy quantifies how chaotic a system is. It is zero for deterministic system that is not chaotic, positive constant for chaotic system and infinite for random process and minimum for uniformly distributed data [85]. It aims at investigating the dynamics of the generating system and eventually confirms its chaotic nature. However it assumes infinite values for processes with superimposed stochastic noise and the limiting length of the available time series introduces approximations to its calculation. These factors make it unable to distinguish processes that differ in complexity. Detailed comparison between linear and nonlinear signal processing is given in Table 2.1.

Table 2.1 Comparison of Linear and Nonlinear signal Processing Techniques

Linear signal processing	Nonlinear signal processing
Finding the signal Separate broadband noise from narrow band signal using spectral characteristics. Method: Matched filter in frequency domain.	**Finding the signal** Separate broadband signal from broad band noise using deterministic nature of the signal Method: Mainfold decomposition or statistics on the attractor .
Finding the space Use Fourier space methods to turn difference equations in to algebraic forms $x(t)$ is observed $X(f) = \sum x(t)\, e^{j2\pi f}$ is used	**Finding the space** Time lagged variables from coordinates for a reconstructed state space in m dimensions . $X(t) = [x(t), x(t+\tau), x(t+2\tau), \ldots\ldots x(t+(m-1)\tau)]$ where τ and m are determined by false nearest neighbours and average mutual information.
Classify the signal • Sharp spectral peaks • Resonant frequencies of the system	**Classify the signal** • Lyapunov Exponents • Fractal Dimension measures • Unstable fixed points • Recurrence quantification • Statistical distribution of the attractor
Making models, predict : $x(t+1) = \sum \alpha_k\, x(t-k)$ Find parameters α_k consistent with invariant classifiers- location of spectral peaks	**Making models, predict :** X(t) $\rightarrow X(t+1)$ $X(t+1) = F[X(t), a_1, a_2 \ldots . a_p]$ Find parameters a_j consistent with invariant classifier - Lyapunov Exponents,fractal Dimension

2.4 METHODS OF CHATTER DETECTION

Apart from different sensors used, a large variety of different signal processing techniques has been reported. Linear signal processing techniques used for chatter detection are power spectral analysis, wavelets analysis and statistical characterization. Smith and Delio [48], Liao and Young [90], Liang et al. [91], Gradisek et al. [58] used the Fast Fourier Transform (FFT) of the measured signal to find the highest peak for detecting chatter in machining. Application of wavelet analysis is implemented by Choi and Shin [43], Sen et al. [92] whereas Li et al. [93] used the coherence in the resulting spectrum of two orthogonal accelerations as indicator for chatter. Onset of chatter is always accompanied by development of synchronized oscillations which results in increased regularity or drop in entropy rate [58, 94]. Therefore quantitative measure for detection of dynamical changes can be effectively used for detection of chatter onset. Grabec et al. [37] suggested the method of Coarse-grained entropy rate (CER) suitable for characterization of short noisy time series calculated from the fluctuations of normal grinding force. For the characterization of regularity of the process he used the concept of mutual information and described the average amount of information of the m^{th} variable from the combination of other (m-1) variables using marginal redundancy. Increase in regularity is indicated by drop in CER. The accuracy of this measure depends on signal- to- noise ratio and when it is low the results are unreliable. As an extension of this work Gradisek [58] presented the method of coarse-grained information rate (CIR) and entropy from power spectrum [58] of normal grinding force for automatic chatter detection. CIR is the average amount of common information contained in the time series and its delayed values quantified using mutual information. Increase in CIR values indicates regular behaviour of the system dynamics. This method is faster compared to CER and is suitable for short data sets. Other important and effective techniques to detect dynamical changes in real world systems are recurrence quantification analysis [87-89], cross correlation sum analysis [95] and nonlinear prediction analysis [96]. These nonlinear methods are based on phase space reconstruction by quantifying 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. Furthermore, these methods give reliable results only when the data is preprocessed and fine tuned.

2.5 Surface Texture Analysis

The surface roughness evaluation finds its main application in the quality inspection of manufacturing processes. In industry the inspection and assessment of surface finish is either performed offline using a stylus type measurement instrument by an operator or online by machine and computer vision. Offline measurement usually requires the removal of the part from the machine, cleaning and testing on an offline surface finish measuring instrument. Inspection requires interruption of the processing and if necessary cleaning of the part prior to inspection. If the part meets the required specification, it is accepted and if not the part or the entire batch may be scraped or reworked. Such methods are slow and obviously not acceptable for real time process control. Current trends show an increased interest in online inspection using non-contact measurement systems. Non-contact measurement is performed using optical sensors. In this approach light interference, light scattering and speckle pattern are used for surface roughness. Luk et.al.[97] have utilized statistical parameter derived from the gray level intensity histograms such as the range and the mean value of the distribution and have observed that they correlate well the surface roughness parameter -Ra value obtained using the stylus method. AL-Kindi [98] have implemented a technique utilizing a roughness parameter based on the spacing between gray level peaks and the number of gray level peaks per unit length of a scanned line in the gray level intensity image to estimate the surface roughness. Jason et al. [99] captured the light intensity scattering pattern from the surface and used it to compute the finish of the rough surfaces. Du-Ming Tsai et al. [100] have employed a two dimensional Fourier transform using both the gray level image and binary image to estimate the surface roughness of castings. Ramamoorthy et al. [101] have also used stereometry techniques to get the three dimensional profiles of such surfaces and successfully estimated the surface area and volume of components. Ramamoorthy et al. [102] estimated optical roughness value -Ga based on the digital images initially magnified using cubic convolution technique and then processed further using the linear edge crispening algorithm. It was reported that the Ga values correlated well with stylus instrument surface roughness value (Ra) measured for the components manufactured using the machining process such as shaping, milling and grinding. Lee et al. [103] have used a self organizing adaptive learning tool called polynomial network to estimate the surface roughness of a component manufactured using conventional processes. Younis [104] has analysed the pattern of scattered light from a surface to derive an optical roughness parameter for different materials. The comparison of optical roughness parameter and the average roughness obtained using a stylus instrument for different materials was found to correlate well and to be highly consistent. Khalifa et.al [105] have calculated Ga index and edge enhancement magnification for study and analysis of surface roughness and concluded that Ga index for chatter rich region is higher than chatter free region. Ramamoorthy et al.[106] have used the group method of data handling to predict the surface roughness using parameters calculated from the images viz. major peak frequency, principal component magnitude squared value and standard deviation. This predicted or estimated value showed concurrence with the values obtained using stylus instrument.

2.5.1 Surface Texture and Non linear Dynamics in Machine

One of the ways in which surface texture is useful is in acting as a fingerprint of the manufacturing process and machine tool behavior. The geometrical profile of a surface gives roughness, waviness and form error information. Roughness is a measure of metal air boundary while form error is the deviation from a perfect Euclidean shape as are the measurements of the deviations from straightness, flatness and roundness. It is reported that the patterns formed on the surface by waviness can be varied and the presence of waviness is detectable visually as a pattern of marks spread more or less periodically along the surface [104]. Modulation effects in waviness usually caused by the tool vibrating radially relative to the component or axially which is mainly due to the self excited chatter between the tool and the work piece.

2.5.2 Speckle Pattern and Surface Roughness

When coherent light gets reflected from a surface with variations in the surface height in the order of wavelength of incident light, speckle pattern is formed due to the interference of reflected wave fronts with random phase and amplitude. Speckle pattern is coded with the information of surface roughness. But it is a random phenomenon due to the randomness in the surface texture. So the information regarding the surface roughness can be extracted only through some statistical parameters. There have been various reported works in which surface roughness is related to statistical parameters of the intensity distribution of speckle pattern. The contrast ratio of the speckle pattern is strongly related to the surface roughness. It is reported that the contrast ratio decreases as the surface roughness in the micrometer scale increases [97, 99]. It is observed that the statistical parameters of optical Fourier transform [107] of the scattered light from a rough surface have got a strong relationship with the roughness of the surface. Statistical parameters derived from the gray level intensity histogram are used to characterize surface texture [97, 105]. Due to chatter vibrations the surface texture of the work piece changes and these variations are generally in millimeter scale. As the depth of cut increases the surface finish is expected to deteriorate, mainly due to the onset of chatter vibrations.

2.6 SPEECH PROCESS AND ANALYSIS

Speech can be broken down in to small segments called phonemes, each of which is unambiguously distinguishable and can be represented by any of a number of different phonetic alphabets. The actual mechanism by which we create a phoneme can be split into two main categories, voiced and unvoiced that can be further split in to vowels, frictives or plosives. Voiced speech or phonation is produced by oscillating the fleshy membranes inside the larynx which are known as the vocal folds. The oscillation is set up by forcing the vocal folds closed which causes pressure to build up below the folds, gradually forcing them to open again allowing the air to flow from the sub glottal region in to the mouth. This rapid air flow creates a Bernoulli force which coupled with the muscular action of the vocal muscles produces the sound. Human speech system behaves like a complicated oscillator that exhibits parameter jumps corresponding to different dynamic regimes (phonemes). Many sources of nonlinearity are involved in the airflow production and laryngeal vibration processes [108]. Although normal phonation and voice disorders can be distinguished very easily, quantification and data distribution are highly desirable from the clinical point of view. The presence of vocal fold pathology can cause significant changes in the normal vibratory patterns of the vocal fold, which in turn can affect the quality of speech production. A mechanical model of speech process is shown in Fig. 2.1. Vocal tract act as the filter to the input given as vocal cord excitation and produces the output as speech signal.

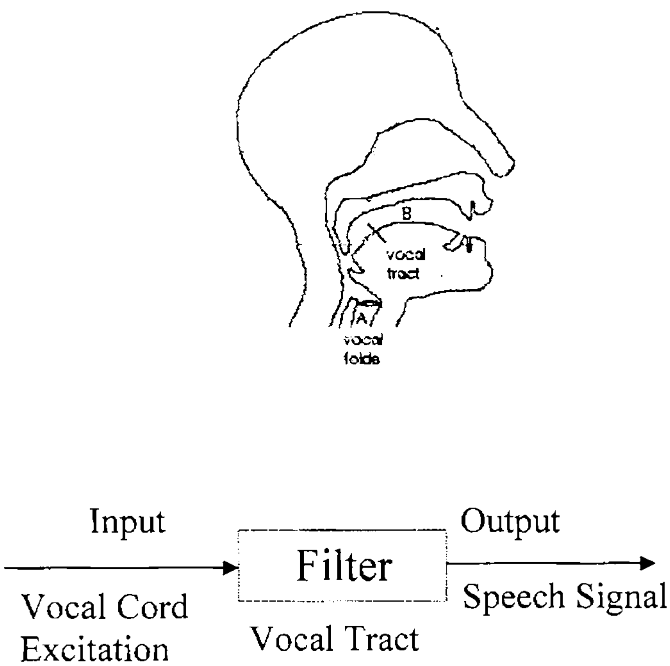


Fig. 2. 1 Mechanical model of speech signal

Speech sounds are produced either by quasi periodic vibrations of vocal cords or by turbulence at some constriction point on the vocal tract [109]. A speech signal can be considered as a time series resulting from complex nonlinear process in the dynamics of larynx.

Evaluation of voice quality is the fundamental approach for diagnosis and treatment of vocal disorders. Various cases of acoustic analysis of normal and pathological voices are reported [110-113]. Acoustic methods have the potential to provide quantitative techniques for clinical assessment of laryngeal and vocal tract function. Though several methods like laryngoscopy, glottography, electromyography, stroboscopy and acoustic analysis[114] currently exists for laryngeal and vocal tract research, acoustic analysis have added advantage over other methods because of its nonintrusive nature. Diagnosis of voice pathologies is mainly done using either subjective technique like evaluation of voice quality by the clinician or invasive methods like laryngeoscopical techniques. Several quantitative measures of voice quality assessment [115-118] are proposed in the recent years which help in the documentation of evolution of the pathological condition. Such measures can prove to be useful for application in fields like preventive medicine and telemedicine. For these reasons modeling of speech process and methods for better understanding of vocal features from voice data has attracted the attention of scientists and technologists for the past few decades. Traditional approach of speech modeling has been linear where the true nonlinear physics of speech production are approximated via the standard assumption of linear acoustics and 1-D plane wave propagation of the sound in vocal tract. A linear model is often easier to estimate and adapt for time-varying systems [119-122]. These approximations lead to the well known linear prediction model for the vocal tract. Despite the limited technological success of the linear model in several applications, such as speech coding, synthesis and recognition, there is strong theoretical and experimental evidence [109,123-128] for the existence of important nonlinear aerodynamic phenomena during the speech production that cannot be accounted for by the linear model. Various factors contributing to nonlinearities in speech production are (i) turbulent air flow through vocal tract, (ii) coupling produced between different parts of vocal tract (iii) neuro muscular response to stimuli [109].

The investigation of speech nonlinearities can proceed in at least two directions: (i) numerical simulation of the nonlinear differential equations governing the 3-D dynamics of the speech air flow in the vocal tract [124,126]. (ii) development of nonlinear signal processing systems suitable to detect such phenomenon and extract related information[128-131]. The phonetory system is time varying and consequently the speech signal is nonstationary. This can be clearly understood if one closely observes the amplitude of the speech samples.

Normal phonation corresponds to an essentially synchronized motion of all vibratory modes. A change of parameters such as muscle tension or localized vocal fold lesions may lead to the desynchronisation of certain modes resulting in bifurcation and chaos [130,132]. The transitions to qualitatively new oscillatory behaviour indicate the suitability of the methods from nonlinear dynamics. Large tension imbalance of left and right vocal fold induces bifurcation to chaos [132]. Harzel et al. [133] have shown that Hopf bifurcations can be found in pathological voices, as well as sudden jump from one limit cycle to another one with different period and amplitude. Different attractors may coexist in nonlinear systems and therefore even extremely tiny changes of parameters like muscle tension may lead to abrupt jumps to other regimes Instabilities due to paralysis, polyps, cancer, papilloma etc produce similar effect and causes abrupt change to irregular regimes from the normal state [134,135]. Quantitative information of these abrupt changes to irregular regimes is still within limited scope. The occurrence of such sudden jumps should be reflected in quantities like entropy and fractal dimension of the attractor. Parameters that characterise the vocal disorders are spectral factor, pseudo entropy, pseudo correlation dimension, first zero crossing of autocorrelation function, first lyapunov exponent, prediction error, jitter, shimmer [136] and peak in the phoneme transition.

(i) **Spectral Factor**: It is the averaged ratio between the amplitude of frequencies under 1KHz and frequencies between 4 and 6 KHz; it is motivated by the effort the sick subjects have to face when they want to talk; this induces instabilities that are reflected by the power spectrum. sick subjects present a smaller value of spectral factor.

(ii) **Pseudo- Entropy**: Entropy averaged for partition radius ε values of 5% to 10% of the variance of the data for embedding dimensions ranging between 2 and 8 [137]. Sick subjects should present larger value compared to healthy people. To overcome the numerical problems encountered in the estimation of the entropy from real data, namely the finite length of the time series and the presence of noise pseudo entropy is introduced.

(iii) **Pseudo- Correlation Dimension**: Correlation Dimension averaged for neighbourhood radius ε values of 5% to 10% of the variance of the data for embedding dimensions ranging between 2 and 8 [137] .Sick subjects should present bigger value compared to healthy people.

(iv) **First Zero Crossing of the Auto Correlation Function**: This parameter is related to the ability of a subject to correctly pronouncing a word. In particular dysphonic patients are not able to isolate every vowel an the resulting time series is more correlated than for healthy subjects. Estimation method is as given in [137]. The first zero crossing for healthy subjects have value between 0.2ms and 0.4 ms while it is greater than 1.2ms for sick subjects.

(v) **First Lyapunov Exponent**: This is a convenient indicator of the sensitivity to small orbit perturbations of characteristic of chaotic attractors, as it gives the average exponential rate of divergence of infinitesimally nearby initial conditions. Some sickness can induce sudden jump from the limit cycle (to which zero maximum Lyapunov exponent is associated) to another one with different amplitude and period (but again with zero maximum Lyapunov exponent); if the jump is due to a bifurcation one can see a positive value. Estimating this quantity, one has to be careful because the Lyapunov exponents for speech data is inconsistent.

(vi) **Prediction Error**: When a well defined attracter is present then the prediction error is small [138]. Normal phonations are indeed to lie with a good approximation on a limit cycle, while sick people commonly produce more disordered time series.

(vii) **Jitter**: This takes in to account the short term (cycle to cycle) variation in the fundamental frequency [132]. Commonly for the healthy voices, the jitter is lower than 1%, while higher values characterise disphonic phonation.

(viii) **Shimmer**: This takes in to account the short term (cycle to cycle) variation in the amplitude of the signal[132]. As in jitter larger values indicate great effort in speaking

(ix) Peak in the Phoneme Transition: The transition between one phoneme and the following shows a much longer transient for sick people. Every phoneme contains a pitch that is repeated a number of time variable between 10 and 20 [139,140]. One has then to identify the time length of such a pitch and to compare the distance between this pattern and one of the same length coming from the same phoneme [136]. Sick subjects present bigger values than healthy people.

Using the above measures a feature space is defined where the healthy and sick cases forms clusters in different regions [136]. For quantifying the vocal disorders a healthy index is defined based on the above measures as the distance of a voice sample from the centre of mass of both healthy and sick clusters in the feature space[136]. Alnoso et al. [141] proposed a classification system to distinguish healthy from pathologic voices using a Neuronal Network (NN). In the feature extraction phase, diverse measures based on the High Order Statistics (HOS) were used in addition to selection of classical voice quality measurements [140]. Various automatic pathology detection methods with different success rates and data bases are also reported [142-144]. These measurements of the voice quality achieve good results, but in exchange for a high computational cost.

The fundamental aim of studying a dynamical system using methods of linear or nonlinear technique is getting a deeper understanding of the dynamical behaviour and the far end aim is charaterising and modeling the dynamical system. Apart from this, another important aspect of such studies is developing new methodologies for technological/ industrial application. This work focuses on the potential application of the simple and robust technique of Permutation Entropy (PE) in characterising system dynamics in varied fields of applications: both mechanical and biological systems. PE is effectively used for detection of epilepsy in noisy EEG signals [145] and for tool flute breakage in end milling [146] from motor current signals.

2.7 SUMMARY

A study of various linear as well as nonlinear techniques in signal processing for the detection of change in dynamics as well as complexity analysis is carried out. Nonlinear time series analysis based on time delay embedding is the conventional method of extracting complexity measures to understand the dynamics of a system.

In the following chapter, the concept of a fast and robust technique suitable for detection of change in dynamics from real world data sets where preprocessing as well as fine tuning becomes expensive in terms of time, quality and money is explained.

CHAPTER 3 - RESEARCH METHODOLOGY

This chapter explains the research methodology adopted for the work presented in the thesis. Here we focuses on the use of a new simple technique based on ordinal patterns in a time series. The quantitative measure proposed by Bandt and Pompe based on the relative frequency of ordinal patterns is termed as Permutation entropy (PE). It is fundamentally a complexity measure for time series. A brief overview of interpretations of entropy and entropy measures are also discussed.

Study and characterization of nonlinear dynamics has been done using various methods. Statistical characterization of the dynamics using the time series of available variable assumes much importance dues to its effectiveness in characterization of different dynamical regimes. One of the statistical concepts of the nonlinear dynamics of complex systems is information entropy. As a complexity measure, the entropy can be generalized to characterise the amount of information stored in the system.

3.1 ENTROPIES IN NONLINEAR SIGNAL PROCESSING

With the aim of charaterising the complexity of dynamical systems, several entropy measures have been defined. Popular among these are approximate entropy (ApEn) [147], sample entropy (SampEn) (148), multiscale entropy (MSE) [149], coarse grained entropy rate [37, 94], coarse grained information rate [58] and permutation entropy (PE) [150]. In general, entropy measures exploit a symbolic representation of a time series. Despite the severe reduction of information these measures are able to enhance the relevant features of a signal. Thus, even tough they do not precisely characterize the generating system they can very well track qualitative changes in time series patterns.

3.1.1. Information and Entropy: Interpretations

Information is one of the many interpretations of entropy. Chronologically it was relatively a very late interpretation. The concept of entropy was conceived and its application to dynamical interpretations was introduced in Clausius's theory of thermodynamics. In this theory, entropy is defined as the measure of unavailable energy which arises due to heat loss as well as other actions such as chemical reactions, mixing, change from solid to liquid to gas. These processes involve not only an increase in entropy but also an accompanying decrease in the orderly arrangement of constituent atoms implying an increase in disorder. For example, atoms and molecules are ordered in a solid thus having low entropy whereas in the case of liquids the entropy will be higher with less ordering of atoms or molecules. Therefore the measurement of entropy became regarded as the measurement of degree of disorder or disorganization of a system.

Still another interpretation is in terms of probability. Just as entropy is maximum for disordered conditions, it is also maximum for equally probable events i.e. when all possible outcomes are equally likely, the probability of any one outcome is low and entropy is high. In contrast, when a biased dice is thrown, the outcome will not be equally probable for all possible outcomes. In such cases, the entropy is lowest. So there is an inverse relation between entropy and probability. Another interpretation based on the probability notion is that of uniformity of the distribution of data. If the data is uniformly distributed among a certain number of compartments, the probability of getting each compartment in a single trial is equal. In that sense, a uniform distribution is a high entropy condition. Conversely, a very non-uniform distribution means low entropy, because one bin has a probability of one and other bins have a probability of zero.

Yet another notion of entropy is uncertainty. The uncertainty can be pertained to the outcome of an experiment about to be run, or it can pertain to the state of a dynamical system. When the outcome of an event is absolutely certain then uncertainty is zero indicating zero entropy. For eg: absolute certainty means probability $P=1$, for which case the entropy will be zero.

Another idea is related to randomly distributed observations versus reliable predictability. When there is disorder, and great uncertainty, predictions cannot be based on any known structure or pattern and can only be done probabilistically. In such cases where predictability is low, entropy will be high. In contrast, something well organized or nearly certain is usually very much predictable resulting in low entropy. The idea of many possible outcomes suggests diversity. Another idea of interpreting entropy is related to the information content of an event. In a given probability distribution there is an information value of so many bits. Furthermore, a relatively large number of bits means a relatively large number of information and vice versa. Hence entropy is the average amount of new information gained from a measurement. Table. 2 shows the different cases where low and high entropies occur with respect to the above discussed interpretations.

Table 3.1 Different cases where low and high entropies occur

High Entropy	Low Entropy
1. Large proportion of energy unavailable for doing work	Large proportion of energy available for doing work
2. Disorder, disorganization, thorough mix	Order, high degree of organization
3. Equally probable events ,low probability of a selected event	Preordained outcomes, high probability of a selected event
4. Uniform distribution	Highly uneven distribution
5. Great uncertainty	Near certainty , high reliability
6. Randomness ,unpredictability	Non randomness, accurate forecasts
7. Much information	Little information

3.1.2 Entropy Measures for Complexity Analysis

Approximate entropy charaterises the regularity of a signal by measuring the presence of similar patterns in a time series. Consider a time series of length N, From this time series short sequences or patterns $x_m(i)$ of length m are constructed and the quantity C_i^m with tolerance r defined as

$$C_i^m(r) = N^{-1}\{number of \quad j \le N-m+1 \quad |d[x_m(i), x_m(j)] \quad \le r\} \qquad (1)$$

is computed for each $x_m(i)$

This quantity measures the regularity of the patterns by comparing them to a given pattern. Here m is the detail level at which the signal is analysed and r is the threshold which filters out irregularities. The regularity parameter ApEn is defined as

$$ApEn(m, r) = \lim_{N \to \alpha} \left[\phi^m(r) - \phi^m(r) \right] \qquad (2)$$

where

$$\phi^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} \ln C_i^m(r) \qquad (3)$$

This gives the relative frequency of finding a vector $x_m(j)$ similar to vector $x_m(i)$ within a tolerance of r and provides a quantitative measure of entropy of the time series.

ApEn statistic gives good results and provides general information about the regularity and persistence of a signal. However, in the above evaluation method, vectors or pattern $x_m(i)$ are allowed to self match and therefore results in biased statistics [147,151,152]. To overcome this drawback, a modification of ApEn algorithm named Sample entropy (SampEn) is developed [148] which avoid this self matching. SampEn shows a relative consistency compared to ApEn [148].

However, this measure strongly depends on length of the series and also gives biased results in the case of irregular signals

As in the case of Komogorov-Sinai entropy, both sample and approximate entropy, provide a measure for the information increase over one step of dimension from m to m+1. To be able to resolve complexity on scales larger than this smallest scale, multiscale entropy is introduced [149, 153]. The efficiency of ApEn and SampEn are enhanced by estimating these measures at different time scales. These measures are widely used for charaterising biological signals in clinical application [154,155].

Coarse-Grained entropy rate (CER) [94] is another measure of regularity calculated based on the mutual information approximated in terms of marginal redundancy for a time series. This is a suitable measure for characterization of time series from experimental data. Accuracy of this measure depends on the signal to noise ratio of the measured data and when it is low it produces unreliable results.

$$CER(m) = \frac{R'(m,\tau_0) - \|R'(m)\|}{\|R'(m)\|} \tag{4}$$

where $R'(m,\tau_0)$ is the marginal redundancy with dimension m and time lag τ_0 and $\|R'(m)\|$ is the norm of marginal redundancy.

Coarse-grained information rate (CIR) [58] 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

$$CIR = \left| I(x(t); x(t+\tau)) \right| = \frac{1}{\tau_{\max}} \sum_{\tau=\Delta\tau}^{\tau_{\max}} I(x(t); x(t+\tau))\, \Delta\tau \qquad (5)$$

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) to define the normalized coarse grained entropy rate (NCIR). For highly regular and thereby predictable systems, NCIR is close to 1 whereas for irregular systems it is close to 0.

Though the above methods give reliable results, their applicability to real world signal analysis is limited due to the sensitivity to noise and computation cost. Therefore, a fast and efficient algorithm which is also robust to noise contamination is very essential for online applications. PE is one such measure suitable for analysis of real world data.

3.2 Permutation Entropy

Permutation Entropy [150]] is a complexity measure which has aspects of both dynamical systems and entropy measures. PE calculation relies on the order relations between neighboring values of a time series. It estimates complexity as the entropy of the distribution of permutations of groups of time samples. PE can

can efficiently detect the regular and complex nature of any signal and extract useful information about the dynamics. Thus the variation of PE as a function of time can effectively indicate dynamical change in any real world data. As this method does not require direct calculations of embedding dimension and time delay, this gives faster output and makes it suitable for online application of real time processes. It is robust against dynamical as well as observational noise [150].

With the onset of chatter, strongly synchronized vibrations buildup and these chatter vibrations presents itself in the dynamics as a lowering of dimensionality of the system and thereby an increase in the predictability of the system dynamics [94]. According to the properties of PE and chatter dynamics, PE is expected to show relatively small change during chatter free cutting. As the chatter vibrations develop during cutting process, due to the increased predictability of the system dynamics PE values are expected to decrease.

In case of vocal disorders, complexities arise due to the intrinsic nonlinear dynamics of the vocal fold movements. These dynamical behaviours can be characterized using nonlinear parameters like entropy and fractal dimension [136]. Due to the increase in irregularity of the system dynamics PE is expected to increase in such cases.

3.2.1 Calculation of Permutation Entropy

Computation of PE is based on comparison of neighbouring 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 on to a symbolic sequence [145,150,156]. 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 neighbour calculation and first minimum of autocorrelation function [137]. For any arbitrary vector X, the components are n number of real values of the time series $\{x_t, x_{t+\tau}, x_{t+2\tau} \ldots\ldots\ldots x_{t+(n-1)\tau}\}$ from time instant 't' to '$t+(n-1)\tau$'. Assuming $\tau = 1$ [58], each point in the n dimensional space represented by its corresponding vector will therefore be equivalent to a short sequence of the time series consisting of n number of real values as $\{x_t, x_{t+1}, x_{t+2}, \ldots\ldots x_{t+(n-1)}\}$. If the components of each vector are arranged in ascending order, it will represent a pattern of evolution. Thus each of the vectors can be considered as a symbolic sequence which will be one of the $n!$ possible permutations of 'n' distinct symbols. The probability distribution of each pattern π can be represented as

$$p(\pi) = \frac{\#\{t \mid t \leq T-n, (x_{t+1,\ldots,} x_{t+n})\, has\, type\, \pi\}}{T-n+1} \qquad (6)$$

where π represents a pattern and # represents the number of occurrences. Permutation entropy of order $n \geq 2$ is defined as the Shannon entropy of the $n!$ patterns or symbolic sequences and can be written as

$$H(n) = -\sum p(\pi) \log p(\pi) \tag{7}$$

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 same probability, $H(n) = \log(n!)$. For a time series representing some dynamics, $H(n) < \log(n!)$. Therefore, normalised PE per symbol of order 'n' is given by $H(n)/\log(n!)$. Thus PE characterizes the system dynamics, with low values indicating regular behaviour. Any increase in PE value will thus represent an 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 Eq.(6) and Eq.(7). Any change in the dynamics of the system will be reflected in the variation of PE with respect to moving window. For a reliable estimation of PE, the window length T should be greater than $n!$ [150]. The order of PE should not be too small as this will not give enough number of distinct states. 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 3 to 8 [150,145]. In our analysis PE of order 6 is used for a window size of 1024 samples for the time series of the audio signal.

As the patterns can be calculated in a very fast and easy way, calculation time of PE is negligibly less compared to other classical nonlinear methods. In this, only two pairs of values are compared at a time. PE based method is 100 times faster than Lyapunov exponent based method [156] due to the fact that neighbourhood searching is not needed. Also we deal with order relations between values instead of values themselves, the permutation entropy is robust with respect to noise corrupting the data.

Permutation entropy has a practically invariance property. If $y_t = f(x_t)$ where f is an arbitrary strictly increasing (or decreasing) real function, then $H(n)$ is same for x_t and y_t. Such nonlinear function f occurs, for example, when measuring physiological data with different equipments. Addition of observational noise causes only a small increase in the value of entropy [150] where as there is hardly any effect on the entropy due to dynamical noise. However in the presence of high noise the ability of PE to distinguish the change in dynamics decreases.

3.2.2 Standard Data Test on PE

Effectiveness of PE is verified on regular chaotic and random data sets. For this, normalised PE for a regular sine wave of amplitude (peak to peak) 0. 2 and a random signal of amplitude 0.2 with 5000 data points each are calculated. Fig 3.1 (a) and (b) shows a sine wave and random signal respectively and their corresponding PE are shown in Fig 3.1 (c) and (d). Permutation entropy for regular sine wave is 0.114 and it is 0.9387 for random signal. Hence it is confirmed that PE values corresponding to regular signal is low whereas for random variation it shows high values.

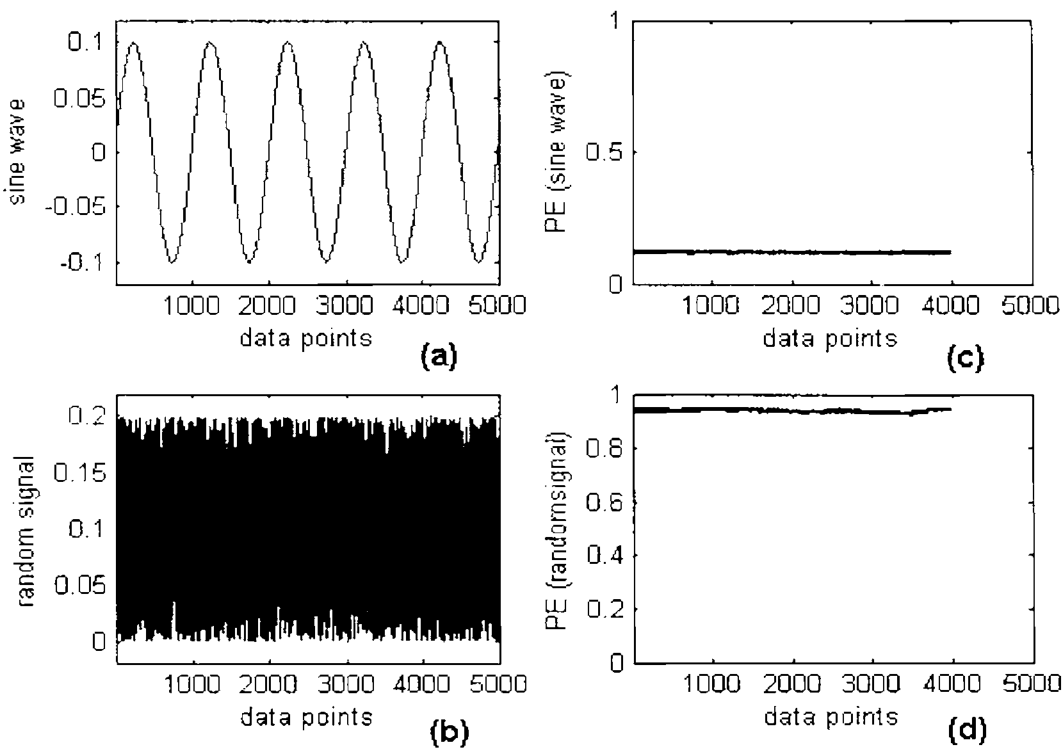


Fig. 3.1 Variation of PE for regular and random signal. (a) sine wave (b) random signal (c) PE for sine wave (d) PE for random signal

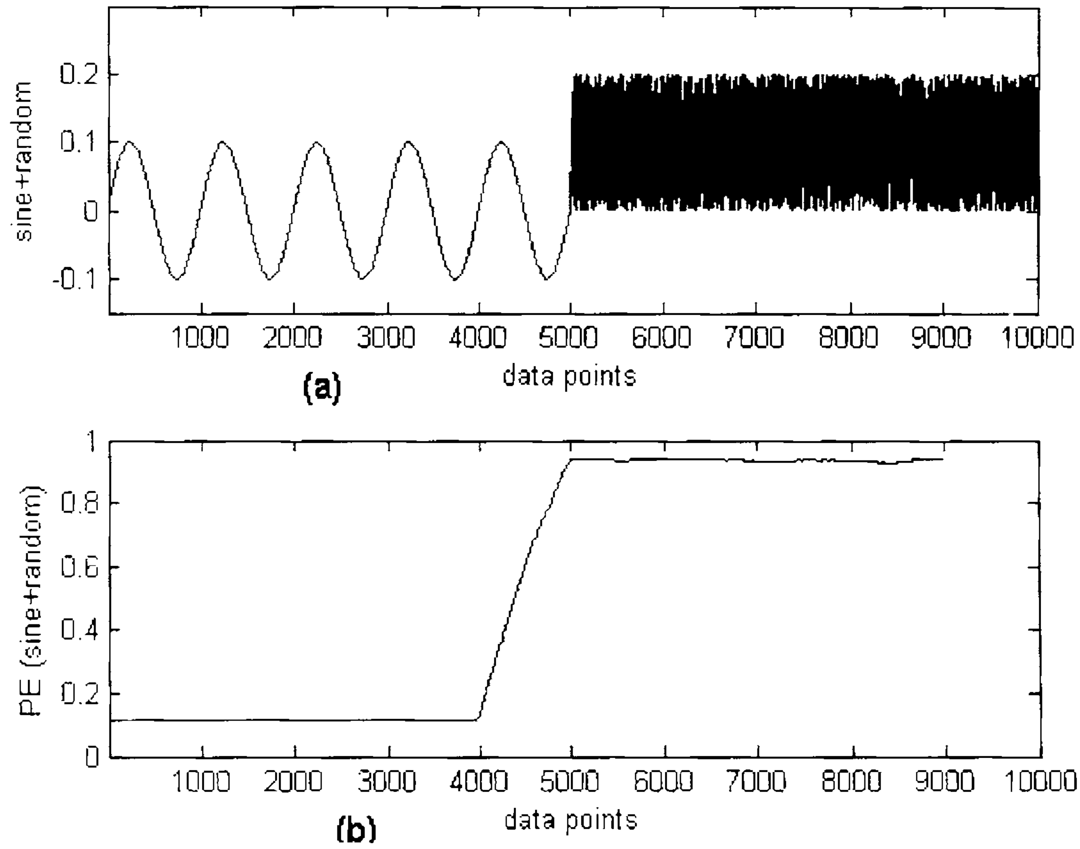


Fig. 3.2 Variation of PE for regular signal connected to random signal (a) sine wave connected to random signal (b) PE for sine wave connected to random signal

When regular sine wave is connected with random signal as given in Fig 3.2(a) the PE value suddenly jumps from 0.114 to 0.9387 as indicated in Fig 3.1(b). This clearly shows that the PE is sensitive to change in regularity. The sudden variation from regular to random state is clearly indicated by the abrupt change in PE values.

To get the feeling of the variations of entropy, results are also verified on chaotic signals with change in dynamics for different parameter values. Bifurcation diagram of logistic map $x_{t+1} = rx_t(1 - x_t)$ is used to study the variation in PE in chaotic signal. Fig. 3.3(a) shows the bifurcation diagram of logistic map for 5000 parameter values corresponding to variation of 'r' from 3.5 to 4. For control parameter r less than 3.57 the logistic map exhibits period doubling phenomenon, and a chaotic dynamics is observed at 3.57. For $3.57 \leq r \leq 4$ the dynamics is more complicated and intricate. This interval of 'r' is not fully occupied by chaotic orbits alone, but many changes take place at different critical values of 'r'. We can clearly see many changes of dynamics as a function of control parameter at 3.5748, 3.5925, 3.6785 and 3.828. At these points the chaotic nature is lost and the behavior is regular or quasi periodic.

PE of order 6 is calculated for non overlapping windows of 1024 samples. Fig 3.3 (b) shows the variation of PE for the same values of 'r' varying from 3.5 to 4. The variation in PE clearly indicates the change in dynamics corresponding to different 'r values'. Corresponding to r values where there is a change in chaotic state PE drops indicating more regularity. This confirms the sensitiveness of PE to change in dynamics of any type of signal.

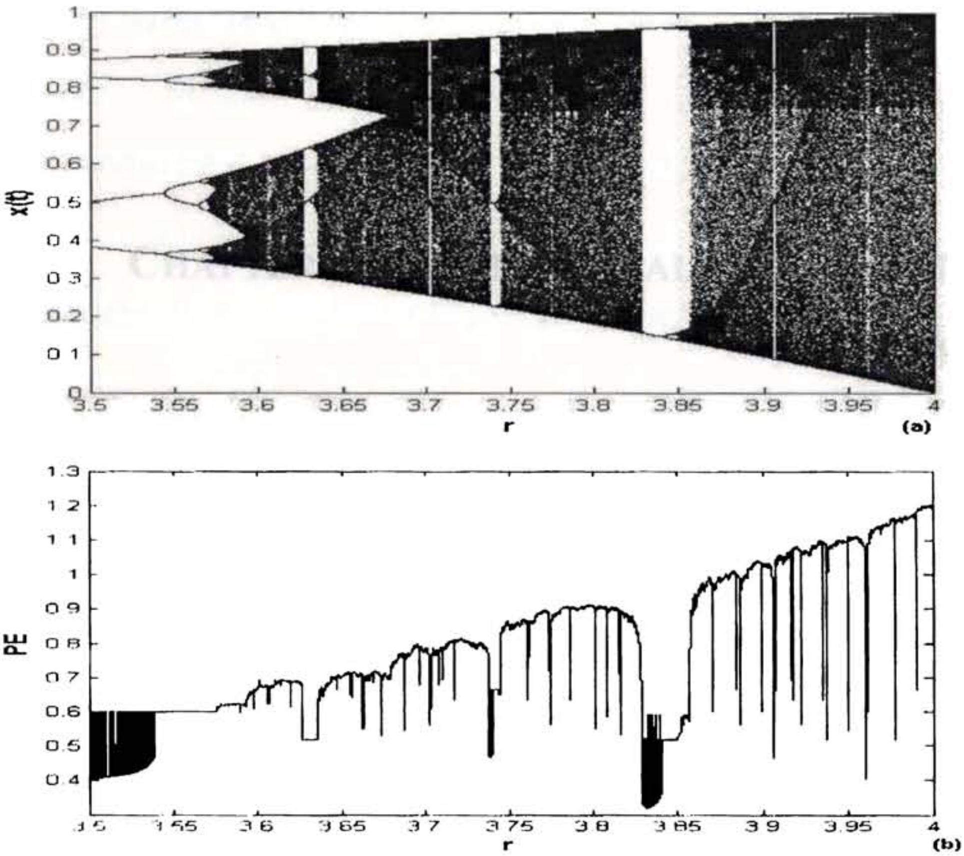


Fig. 3.3 Logistic equation for varying control parameter 'r'
(a) Bifurcation diagram (b) Variation of PE

3.3 Summary

Various entropies are used for quantifying the complexity of a dynamical system. Each one has its own advantages and disadvantages. Calculation of permutation entropy is based on the comparison of neighbouring values in the time series. Tests on different types of data shows that PE is a fast and robust technique suitable for online application of detection of change in dynamics. Details of experimental setup and data acquisition are explained in the coming chapters.

CHAPTER 4: EXPERIMENTAL SETUP AND DATA ACQUISITIONS

In this chapter, the experimental set up and the data acquisition systems used in this work are explained. Section 1 deals with the work piece description and data acquisition using microphone and current sensor in turning process. Section 2 describes the experimental set up of speckle photographic method used for surface texture analysis. Section 3 focuses on data acquisition for speech signal.

4.1 EXPERIMENTAL SETUP OF TURNING PROCESS

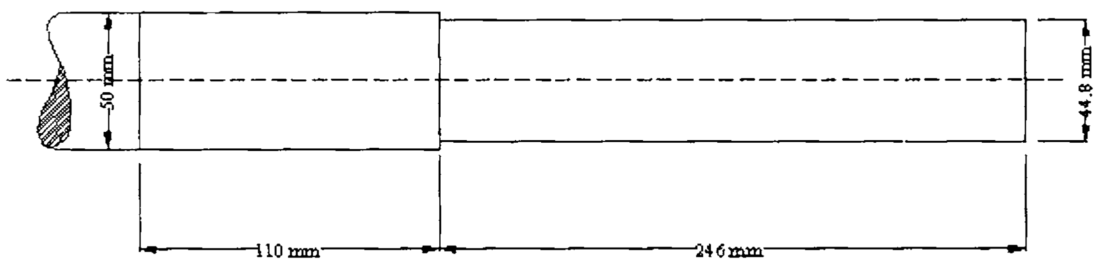
The experimental setup for turning process consists of the heavy duty lathe, work pieces, two sensors viz, unidirectional microphone and current sensor with two PCs. Experiments are conducted for acquiring data for sudden increase in depth of cut and continuous increase in depth of cut on the selected work piece.

4.1.1 Description of Machine and Work Piece

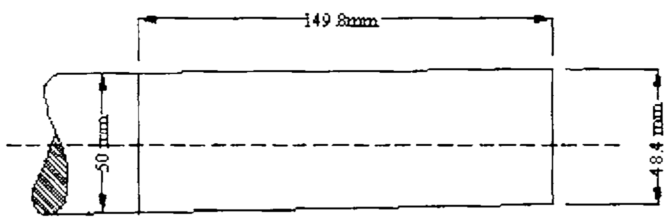
Single point turning experiments are performed on a 3 phase, 3.7kW, 1400 rpm PSG heavy duty lathe using CNMG 120408 PM carbide inserts with standard tool holder. The work pieces are cylindrical and conical and are made of mild steel. The work pieces are held firmly between centers; a four jaw chuck and a revolving centre. The cutting factors, speed and feed rate are maintained constant at 560 rpm and 0.06mm/rev for all sets of experiment while the depth of cut is varied as designed in the particular set. No coolants or lubricants are used in the experiment. The experiments are carried out in two different cutting conditions

(a) A 356mm long cylindrical work piece with 50mm diameter is machined with 0.1 mm depth of cut for a length of 110mm. The depth of cut is suddenly changed to 2.6mm and is maintained for the next 246mm. Figure 4.1 (a) shows the work piece geometry for this sudden increase in depth of cut from 0.1mm to 2.6mm.

(b) A conical work piece of 149.8 mm length and initial diameter of 50mm is machined with continuous increase in depth of cut from 0.1mm to 0.8mm. Figure 4.1 (b) shows the work piece geometry for continuous increase in depth of cut from 0.1mm to 0.8mm.



(a)



(b)

Fig .4.1 Workpiece Geometry (a) sudden increase in depth of cut from 0.1mm to 2.6mm (b) for continuous increase in depth of cut from 0.1mm to 0.8mm

4.1.2 Description of Data Acquisition System

A unidirectional microphone for the measurement of audio signal and a current sensor to measure the line current drawn by the lathe drive motor are employed for data acquisition. Measurements of audio and current signals are made simultaneously from these sensors for the same cutting conditions.

(i) Audible sound signal from Microphone

Fig. 4.2 shows the schematic of experimental set up for acquiring audio signal in turning. The audio signals are captured using unidirectional microphone CSM-990, AHUJA, with frequency response 20-18000 Hz. This signal is recorded in a standard PC using a soundcard with data pre processing of low pass antialiasing. These signals are sampled at 11 KHz to generate the time series. 15 records are acquired for each cutting process and the corresponding time series are used for PE analysis.

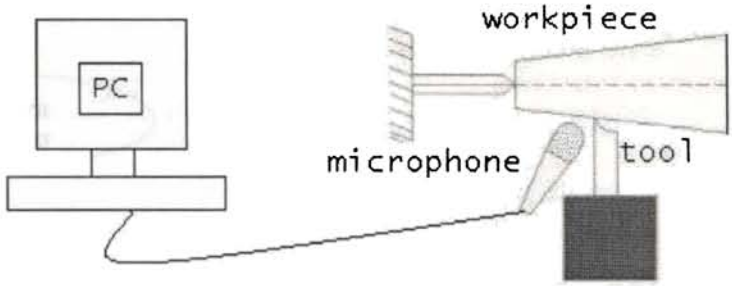


Fig. 4.2 Schematic of Experimental set up for data acquisition using microphone

(ii) Spindle Drive current from current sensor

Data acquisition system for spindle drive motor current uses a 3 phase line current sensor to measure the current drawn by the lathe drive motor. The sensor consists of three current trasnsformers (CT) having an output range of $\pm$5volts. Flow diagram for the sensor set up is given in Fig. 4.3.

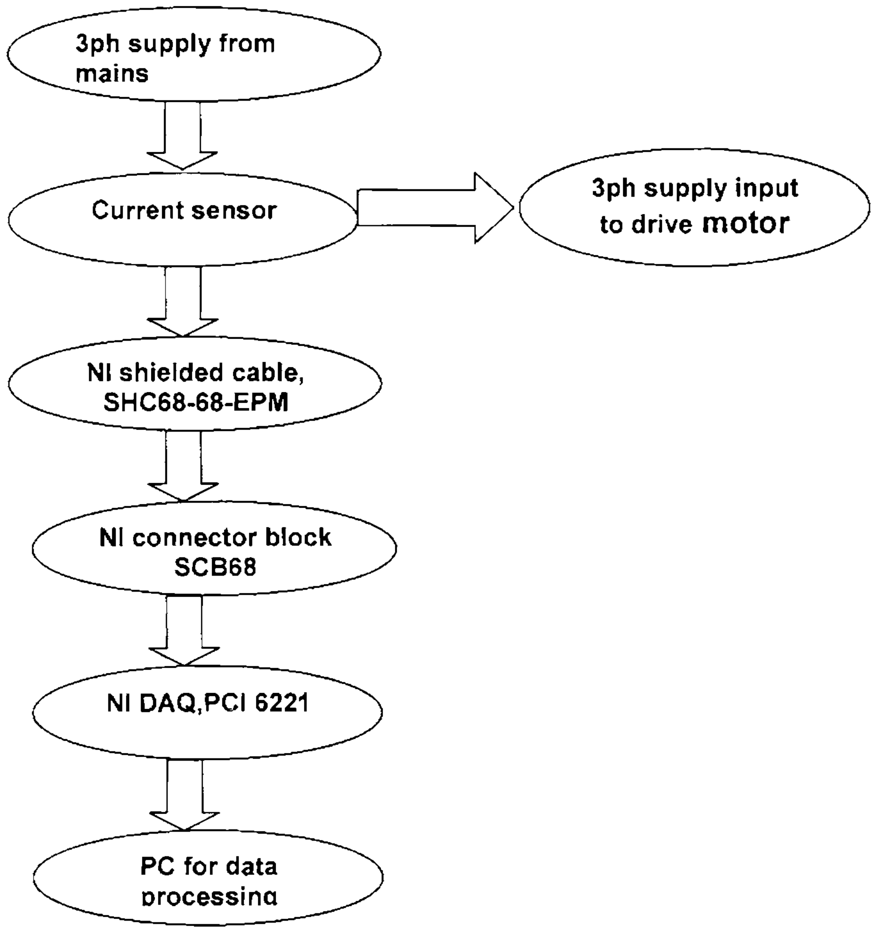


Fig 4.3 Data acquisition flow diagram for the current sensor

The analog voltage signal from the output of the CT is sent to DAQ NI PCI 6221 through NI SHC68-68-EPM and SCB68 for converting into digital domain. The sampling rate is fixed at 1 KHz to cover the entire frequency range of the signal. The digitized data is recorded in the PC using NI LabVIEW

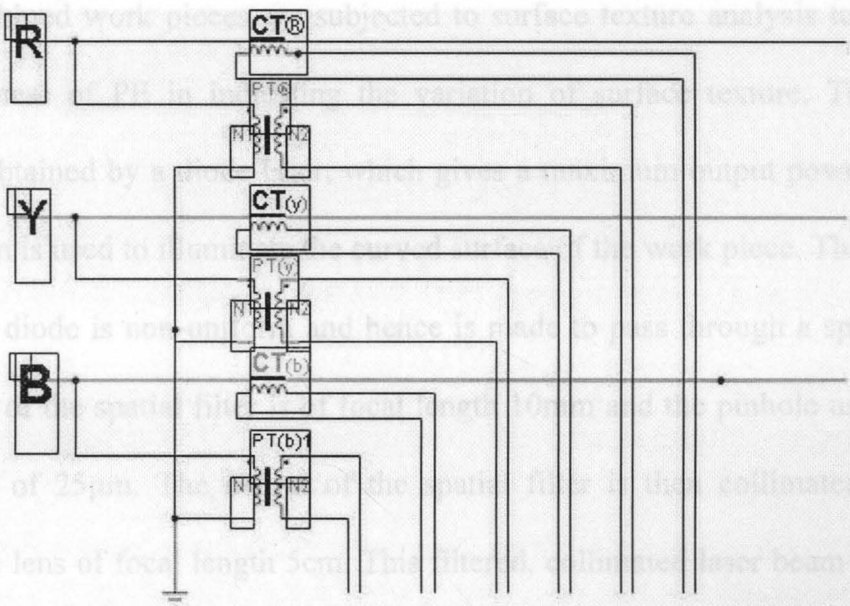


Fig 4.4 Block schematic of the voltage and current measurement setup

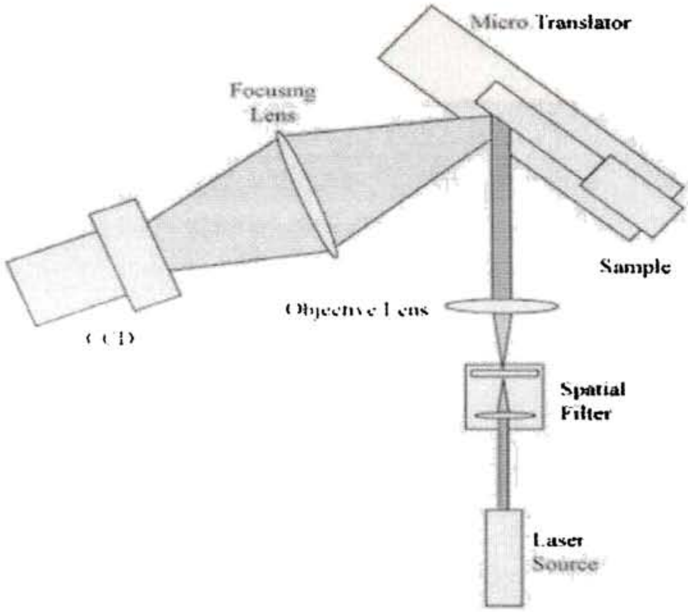
The voltages and currents in each phase is measured using three potential and current transformers with an output range of ± 5 volts. Figure 4.4 shows the connection diagram for this measurement.

4.2 EXPERIMENTAL SETUP OF SPECKLE PHOTOGRAPHIC METHOD

The experimental setup for speckle photographic method consists of laser source, spatial filter, objective lens, micortranslator, focusing lens, CCD camera and a PC.

4.2.1 Laser Speckle from Machined Work piece

The machined work pieces are subjected to surface texture analysis to study the effectiveness of PE in indicating the variation of surface texture. The speckle pattern obtained by a diode laser, which gives a maximum output power of 5mW at 633 nm is used to illuminate the curved surface of the work piece. The output of the laser diode is non-uniform and hence is made to pass through a spatial filter. The lens of the spatial filter is of focal length 10mm and the pinhole used has the diameter of 25μm. The output of the spatial filter is then collimated using an objective lens of focal length 5cm. This filtered, collimated laser beam is made to fall on the sample for the roughness detection. The light is incident on the sample at an angle of 48.7°. The collimated incident light scatters off the rough surface of the sample. This scattered light is focused using a focusing lens of focal length 10cm and the resulting subjective speckle pattern is recorded using a CCD array. The CCD which is used for recording is a VGA type 1/3 inch Sony CCD, with 8bit mono recording and with 7 micrometer pixel size. The exposure and the gain of the CCD are adjusted so as to ensure that the recorded intensity lies well below the saturation value. Figure 4.5 shows the schematic of the experimental setup for data acquisition using laser speckle photographic method.



4.5 Schematics of Experimental set up for data acquisition using laser.

The speckle pattern is recorded at an angle of 90^0 from the incident beam. The position of the focusing lens and CCD array is adjusted in such a way as to get the maximum contrast speckle pattern. The light distribution on the CCD is viewed through an IBM compatible computer. The sample is scanned along its length over a few centimeters using a micro-translator. These speckle images are stored in the computer and are used for surface texture analysis. Fig 4.6 shows the photograph of the experimental set up used for acquiring speckle patterns from speckle photographic method.

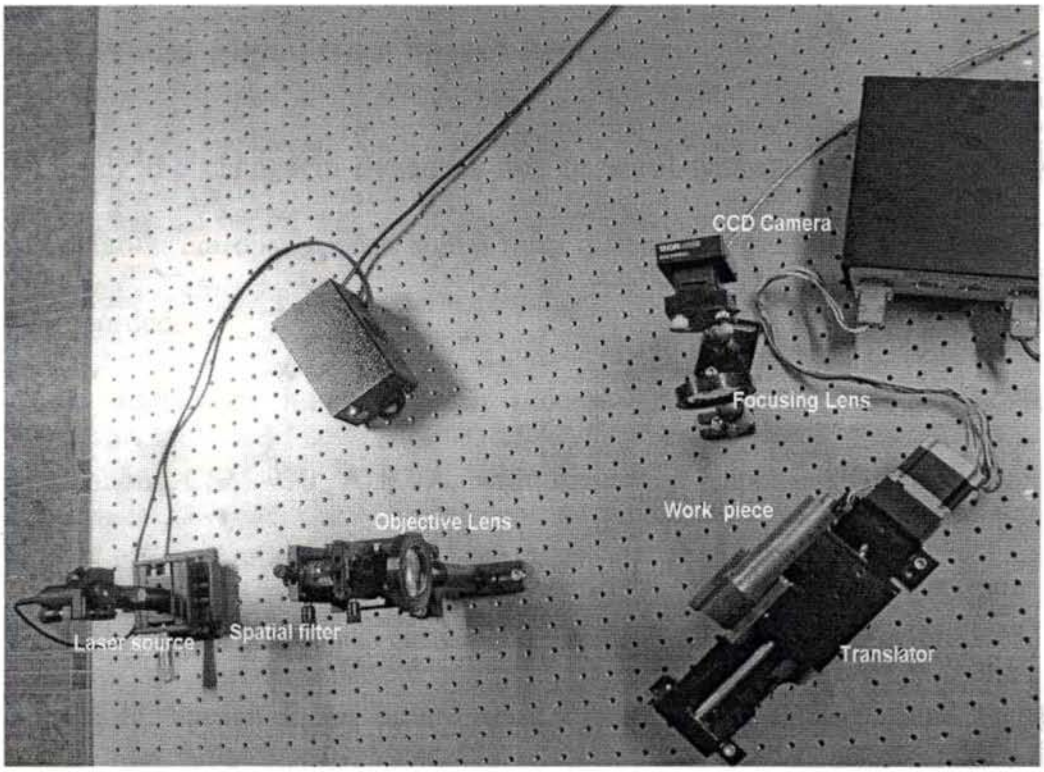


Fig 4.6 Photograph of the experimental setup for recording speckle pattern.

4.3 DATA ACQUISITION SYSTEM FOR SPEECH SIGNAL

The data acquisition system for speech signals consists of a unidirectional microphone and a PC. The vocal sound signals are recorded from the subjects in a sound proof room.

4.3.1 Audio Signal from Speech Process

To study the change in dynamics due to vocal pathology and its reflection in permutation entropy, speech signal from different normal and pathological cases are recorded.

Audio signals of human speech process are acquired using unidirectional microphone CSM-990, AHUJA, with frequency response 20-18000 Hz. Audio signals corresponding to three Malayalam alphabets "A","E", "U" are used for analysis. These phonemes correspond to different patterns of vibrations of the vocal fold. Speech signal from 3 normal male, 3 normal female and 3 abnormal (2male and one female) subjects are recorded using unidirectional microphone in a sound proof room. These signals are sampled at 11 KHz and recorded in a standard PC using sound card. The amplitude time series of these signals are used for PE analysis.

4.4 SUMMARY

Audible sound signals and spindle drive current signals are recorded simultaneously in two cases of cutting (i) for sudden increase in depth of cut and (ii) continuous increase in depth of cut. Unidirectional microphone and current sensors are used for acquiring audio and current signals respectively. Speckle photographic method is used to capture laser speckle pattern in a CCD camera from the surface of the machined work piece. The different signals are stored in PC to generate the time series for further analysis. Speech signals from normal as well as abnormal subjects are recorded using unidirectional microphone for evaluating the underlying dynamics. Results of these experiments are explained in the next two chapters.

CHAPTER 5 - RESULTS AND DISCUSSIONS ON TURNING PROCESS

In this chapter, results of PE analysis using audio signals and current signals in two different cutting conditions are discussed. These results are verified using standard linear and nonlinear techniques. The results of surface texture analysis using PE are established with the help of standard optical roughness indicator. Here the results are discussed in three sections. First section explains the audio signal analysis for sudden and continuous change in depth of cut. Results based on the current signal analysis are detailed under second section. Third section deals with the PE based analysis of surface texture. Surrogate data test is carried out on the acquired signals for confirming the nonlinearity of the signals.

Audio and current signals are widely used for characterising the system dynamics. The use of microphone and current sensor is relatively ideal for detection of vibration during the machining process as they have the best features to detect chatter.

Experiments are conducted on a 3 phase, 3.7kW,1400 rpm PSG heavy duty lathe using CNMG 120408 PM carbide inserts with standard tool holder. Samples of work pieces are made of mild steel. Feed rate of 0.06mm per rev and speed of 560 rpm are maintained through out the experiment. Audio and current signals are acquired for different cutting conditions. Sampling rate of 11 KHz and 1 KHz are used for audio signal and current signal respectively . PE analysis is carried out on the following data sets

(i) Audio signal analysis of sudden change in depth of cut

(ii) Audio signal analysis of continuous change in depth of cut

(iii) Current sgnal analysis of sudden change in depth of cut

(iv) Current signal analysis of continuous change in depth of cut

5.1 AUDIO SIGNAL ANALYSIS

PE analysis is carried out on audio signals captured from sudden change in depth of cut as well as continuous increase in depth of cut.

5.1.1 PE Analysis of Sudden Change in Depth of Cut

In this experiment a constant depth of cut of 0.1mm is maintained up to a length of 110 mm of the work piece and suddenly changed to 2.6mm at this point. Above this point constant depth of cut of 2.6mm is maintained up to a length of 246mm. Audio signal acquired using unidirectional microphone is used for the analysis. The signal is sampled at 11 KHz to generate the time series.

For permutation entropy based analysis, the time series is first partitioned into non overlapping windows of 1024 samples acquired within a time span of 93.1 ms. Normalised PE value is calculated for every window. Variation of PE with respect to moving windows is used for detection of onset of chatter. Permutation entropy for order 5, 6 and 7 with different window sizes of 1024 and 2048 gives consistent results. Here we present the results of PE of order 6 for a window size of 1024 samples of the time series of the audio signals. These values are found to be the ideal choice for getting optimum speed of calculation with minimum memory restrictions.

Fig. 5.1 shows the variation of PE with respect to length of the work piece for sudden change in depth of cut from 0.1mm to 2.6 mm. For a length of work piece below 110mm corresponding to 0.1mm depth of cut, it can be observed that there is no significant change in dynamics as indicated by PE values. Between

110.11mm and 113.7mm 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 91microsecond. 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 window 213 and 220. These seven windows correspond to 7168 samples. Therefore the change in dynamics can be detected within 652ms. This is comparable to the response time of conventional manufacturing machines to external control signals. It is clear from the results that the PE values are available at the same instant at which the data points are acquired.

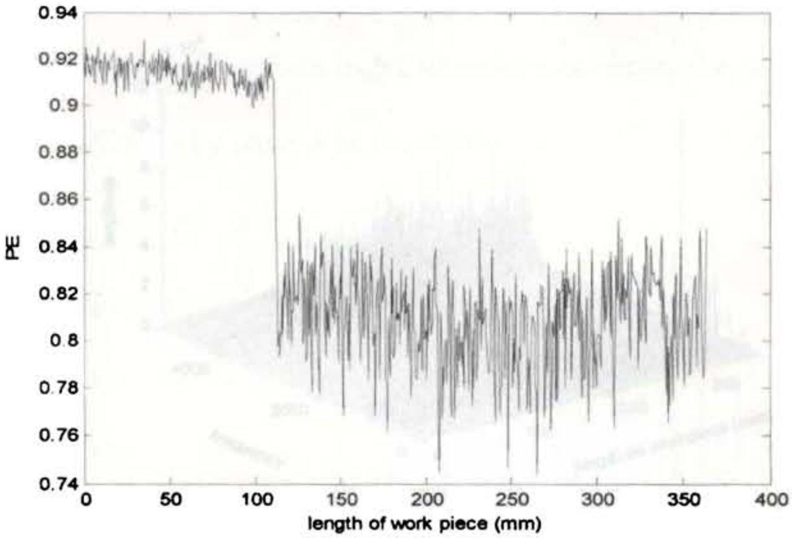


Fig. 5.1 Variation of PE for sudden change in depth of cut from 0.1mm to 2.6 mm

To verify the results obtained using PE, conventional linear technique of Fast Fourier Transform is used. Waviness of a signal profile is easier to assess from the amplitude spectrum calculated by the Fourier transform. In this example, the amplitude spectra of the profile are flat with no dominant spectral peak indicates chatter free region or low amplitude random like behaviour.

The frequency spectrum of data with respect to length of the work piece is shown in Fig. 5.2. The spectra for a length 112.9 mm of the work piece do not contain any dominant peaks. Above this point the spectra contains more number of dominant peaks. The development of harmonic peaks is indicative of more regular behaviour which in turn represents the presence of chatter vibrations.

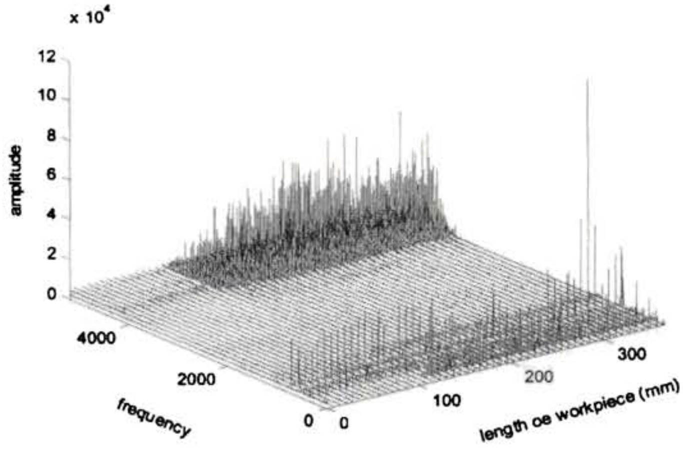


Fig. 5.2 FFT of audio signal for sudden change in depth of cut from 0.1mm to 2.6 mm

The above results are also verified using normalized coarse-grained information rate (NCIR) using Eq.5 of chapter 3. 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+τ), CIR is defined as the norm of mutual information.

The software migram from CRP toolbox [157] is used to calculate $I(x(t);x(t+\tau))$ of Eq. 5 of chapter 3 for CIR. Maximal time delay of 50 and embedding dimension of 2 are used for NCIR calculation [37]. Fig. 5.3 shows the variation of NCIR with respect to length of the work piece. For the initial range of cutting below the length of 110.9mm of the work piece the NCIR values remains at low values. The depth of cut is maintained at 0.1mm 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 115.1mm. 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.

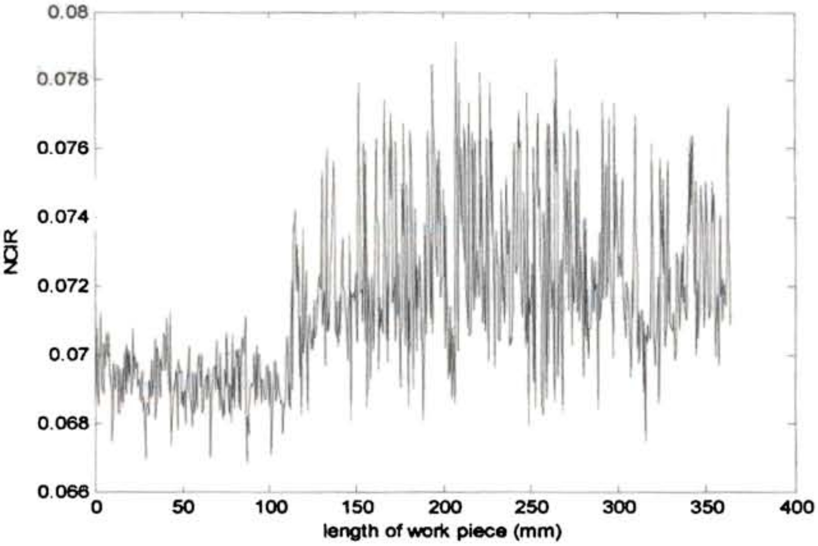


Fig. 5.3 NCIR of audio signal for sudden change in depth of cut from 0.1mm to 2.6 mm

5.1.2 PE Analysis of Continuous Increase in Depth of Cut

In this experiment the depth of cut is continuously varied from 0.1 to 0.8mm over a 149.8 mm long work piece thereby slow and smooth increase in depth of cut is maintained throughout the cutting process. The acquired audio signal is converted to a time series of length 4772633 samples corresponding to 149.8mm length. Fig.5.4(a) and (b) shows the variation in PE with respect to depth of cut from 0.1 to 0.4mm and from 0.4mm to 0.8 mm respectively. It can be observed from Fig.5.4(a) 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. 5.4(b), 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 behaviour is not sustained for long and is soon followed by sharp jumps indicating bursts of chatter up to 0.49mm. 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 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 91microsecond. The time required for estimating PE values of one window is of the order of nanoseconds and can be neglected compared to the time for acquiring the corresponding data points.

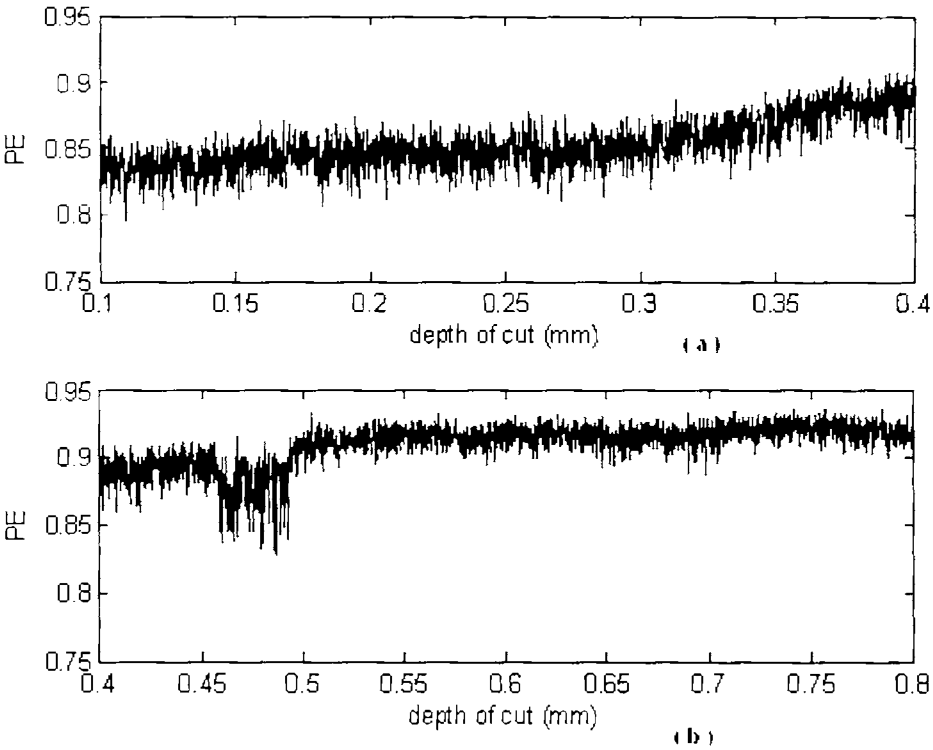
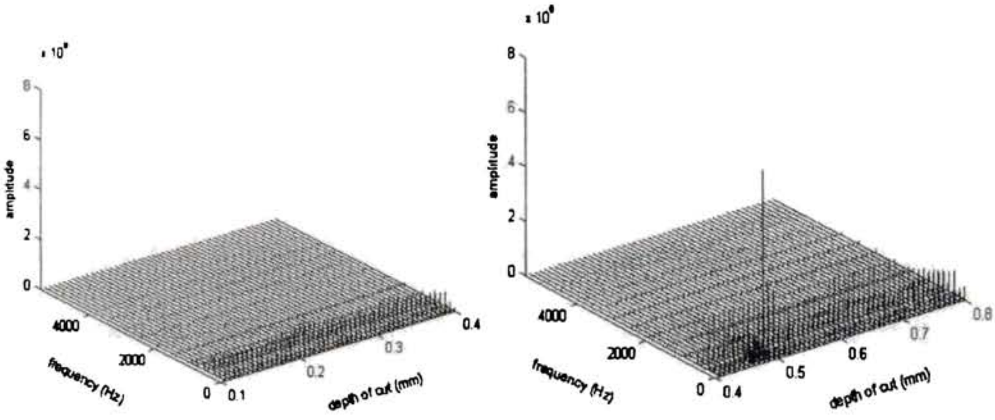


Fig. 5.4 Variation of PE for continuous increase in depth of cut from (a) 0.1mm to 0.4mm and (b) 0.4 mm to 0.8mm.

The sudden drop in PE value occurs within an interval of time required for acquiring 5120 samples which corresponds to 466ms. The chatter detection speed of PE at this sampling rate is more than sufficient for use with an online setup.

Fig. 5.5 (a) shows the frequency spectra with respect to depth of cut varying from 0 to 0.4mm Fig. 5.5(b) that of 0.4mm to 0.8mm. The spectra in Fig. 5.5 (a) do not contain any strong peaks which is typical of chatter-free dynamics. It is clear from Fig. 5.5(b) that around 0.46mm 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 as in Fig. 5.4(b).



(a) **(b)**

Fig. 5.5 FFT of audio signal (a) for continuous increase in depth of cut from 0.1mm to 0.4mm and (b) for continuous increase in depth of cut from 0.4mm to 0.8mm

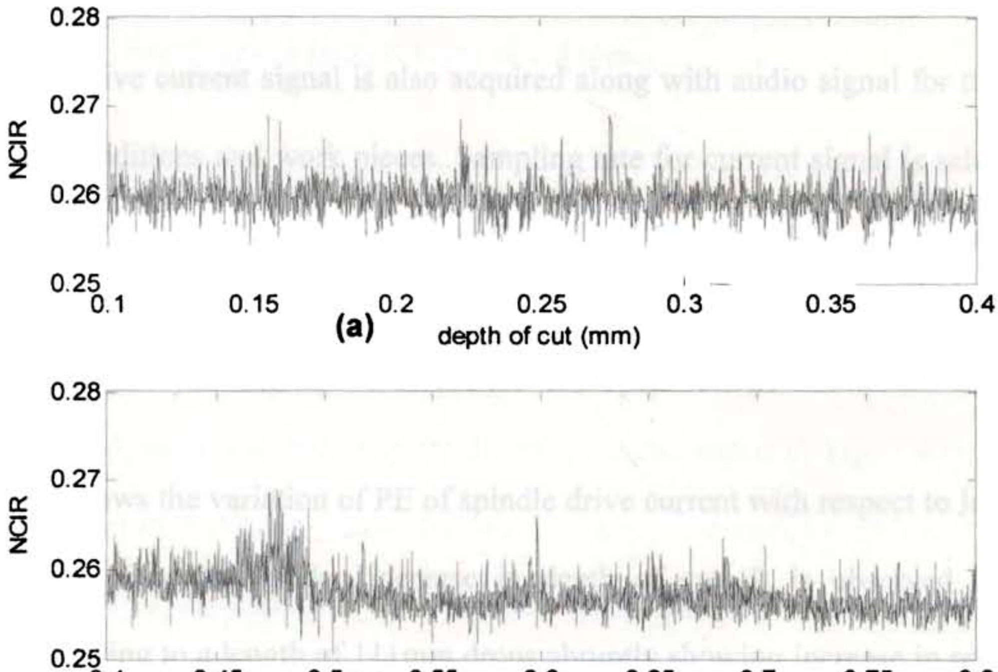


Fig. 5.6 NCIR of audio signal (a) for continuous increase in depth of cut from 0.1mm to 0.4mm (b) for continuous increase in depth of cut from 0.4mm to 0.8mm

Fig. 5.6 (a) shows the variation of NCIR for the above signal for depth of cut from 0 to 0.4 mm and Fig. 5. 6 (b) shows the variation of NCIR for depth of cut from 0.4mm to 0.8mm. It can be inferred from the figure that NCIR values show an increase at 0.46mm 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. 5.6 (b) confirms the change in dynamics indicated by the drop in PE in Fig. 5.4 (b)

5.2 CURRENT SIGNAL ANALYSIS

Spindle drive current signal is also acquired along with audio signal for the same cutting conditions and work pieces. Sampling rate for current signal is selected as 1000 Hz. PE of order 6 for moving window of 1024 samples is used for analysis.

5.2.1 PE Analysis of sudden Increase in Depth of Cut

Fig 5.7 shows the variation of PE of spindle drive current with respect to length of the work piece for sudden increase in depth of cut. It is observed that PE corresponding to a length of 111mm drops abruptly showing increase in regularity of the dynamics thereby indicating the onset of chatter. This result concurs with that obtained from PE of audio signal in Fig 5.1. The drop in PE is obtained within one window corresponding to 1024 sample points. With the sampling rate of 1

KHz, the data acquisition time for 1024 samples is 1s. As the calculation time for PE is negligible compared to data acquisition time, the detection time using current signals turns out to be 1s.

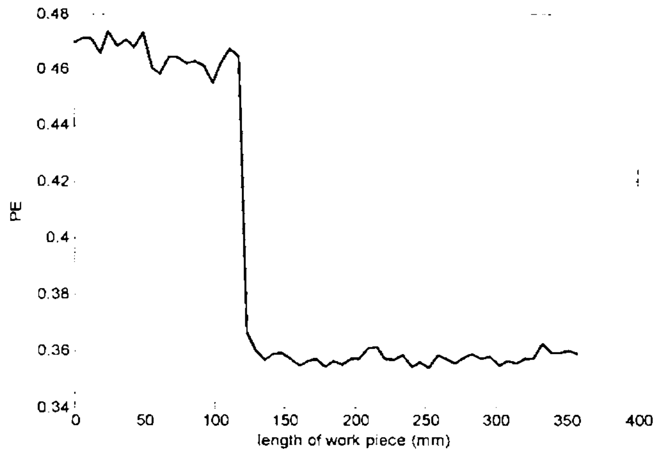


Fig. 5.7 Variation of PE of spindle drive current for sudden change in depth of cut from 0.1mm to 2.6 mm

5.2.2 Current Signal Analysis of continuous increase in depth of cut

Fig 5.8 shows the variation of PE of spindle drive current with respect to depth of cut for taper cut. The drop in PE at 0.46 mm depth of cut corresponds to the change in dynamics as indicated by the PE of audio signal in Fig. 5.4 (b). Small variations of PE values in the chatter free region as indicated in Fig5.7 and Fig. 5.8 can be due to the influence of high starting current drawn by the motor. The sudden drop in PE value occurs within an interval of time required for acquiring 4096 samples which corresponds to 4s. The chatter detection speed of PE from current at this sampling rate is low when compared with that of audio signal.

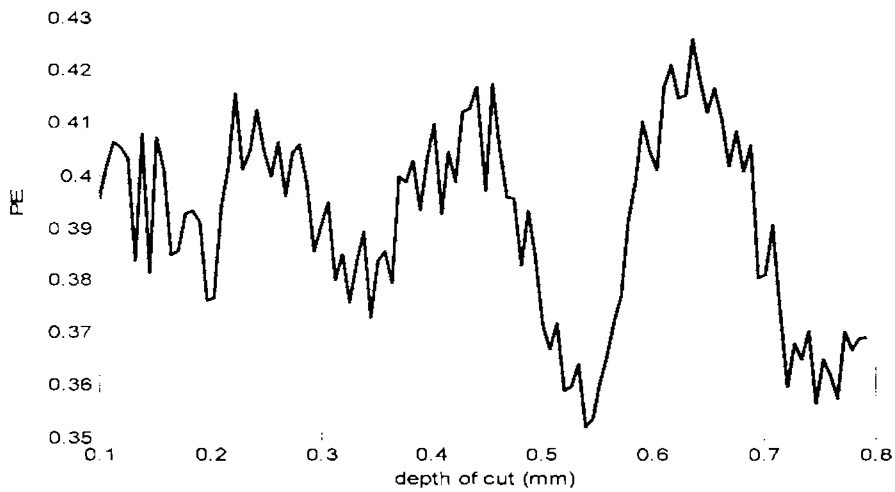


Fig. 5. 8 Variation of PE of spindle drive current for taper cut for depth of cut from 0.1mm to 0.8mm

5.3 SURFACE TEXTURE ANALYSIS

Speckle images of light reflected from the work piece machined on a lathe for increasing depth of cut from 0.1mm to 0.8mm are recorded as explained in section 4.2. Each speckle image is digitized and converted to matrices of size 480X640 elements of which falls in the range of 0-255 gray levels. The mean gray level intensity of this speckle pattern is calculated to generate the corresponding time series data for increasing depth of cut. The mean grey level of the histogram is defined as

$$\mu = \frac{\sum_{i=0}^{255} F_i X_i}{\sum_{i=0}^{255} F_i} \qquad (8)$$

where F_i is the number of pixels having X_i gray levels. Change in surface texture is detected using the complexity measure PE of this time series. PE of order 4 with window size of 64 is selected for speckle analysis.

Fig.5.9 (a) and 5.9 (b) shows the variation in PE with respect to depth of cut from 0.1 to 0.4mm and from 0.4mm to 0.8 mm respectively. It can be inferred from this figure that PE obtained from mean gray level intensity remains almost a constant with only slight variation in its value up to 0.4 mm depth of cut indicating regularity in the reflected light which is indicative of a smooth surface. Between 0.4mm and 0.45mm, there is a sudden increase in PE value which indicates a change in the dynamics of the system. The sudden increase of PE indicates an increase in irregularity thereby indicating an increase in roughness. Variation of PE in the chatter region is much larger compared to the chatter free region. This transition in dynamics is verified from the variation in waviness of the surface. The mean and standard deviation of the PE values of chatter and chatter free regions are calculated for a further confirmation of the results. For chatter free region the mean value of PE is 0.7 with a standard deviation of 0.03 whereas the mean and standard deviation of chatter free region lies at 0.61 and 0.06. This substantiates the inference that in chatter region the PE values are lower than that of chatter free regions with larger variations. The larger variation in PE values in the chatter region further indicates the variations in ordinal patterns in the reflected light intensity which further indicates the waviness of surface texture.

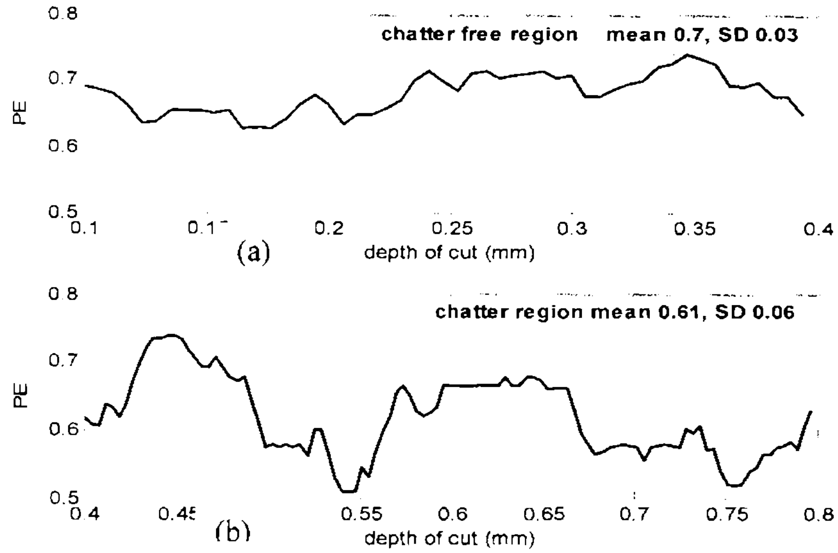


Fig. 5.9 Variation of PE with respect to depth of cut (a) for chatter free region (b) for chatter region

To confirm the results of PE analysis, surface roughness of the workpiece corresponding to depth of cut from 0.3mm to 0.6mm is analysed using surface roughness parameter R. The information regarding the surface roughness can be extracted through statistical parameter R [97,105]. From the gray level histogram of the speckle pattern optical roughness parameter R is calculated using the equation [97]

$$R = \frac{SD}{RMS} \qquad (9)$$

where SD is the standard deviation of the distribution and RMS is the root mean square height of the distribution given as follows

$$SD = \left(\frac{1}{N-1} \sum_{i=0}^{255} F_i (X_i - X)^2 \right)^{1/2} \qquad (10)$$

$$RMS = \left(\frac{1}{N} \sum_{i=0}^{255} F_i^{\,2} \right)^{1/2} \qquad (11)$$

where $X = \frac{1}{N} \sum_{i=0}^{255} F_i X_i$ and $N = \sum_{i=0}^{255} F_i$

Fig. 5.10 shows the variation of R with respect to continuous increase in depth of cut from 0.3 to 0.6 mm. The lower values of R in the initial region of the graph shows relatively smooth surface texture. At 0.45mm depth of cut, R shows an increasing tendency indicating decrease in surface finish. The value of R reaches a maximum at 0.49 mm depth of cut indicating poor surface finish. Above this point R again drops to lower values indicating an increase in surface finish. The lowering of surface finish as indicated by increase in R between 0.45mm and 0.49mm depth of cut corresponds to the chatter region in Fig. 5.4. The repeatability of the experiment was ensured by repeating the experiment for different samples. Similar characteristics were observed for various samples.

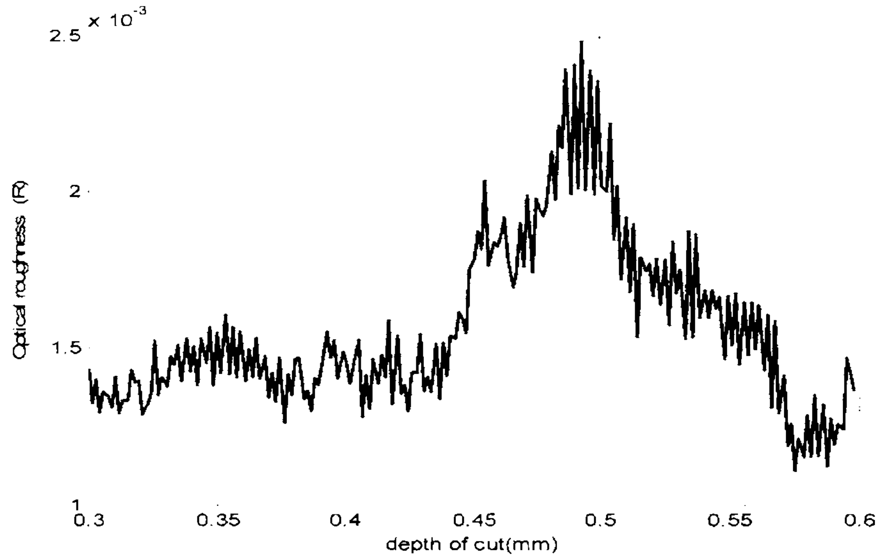
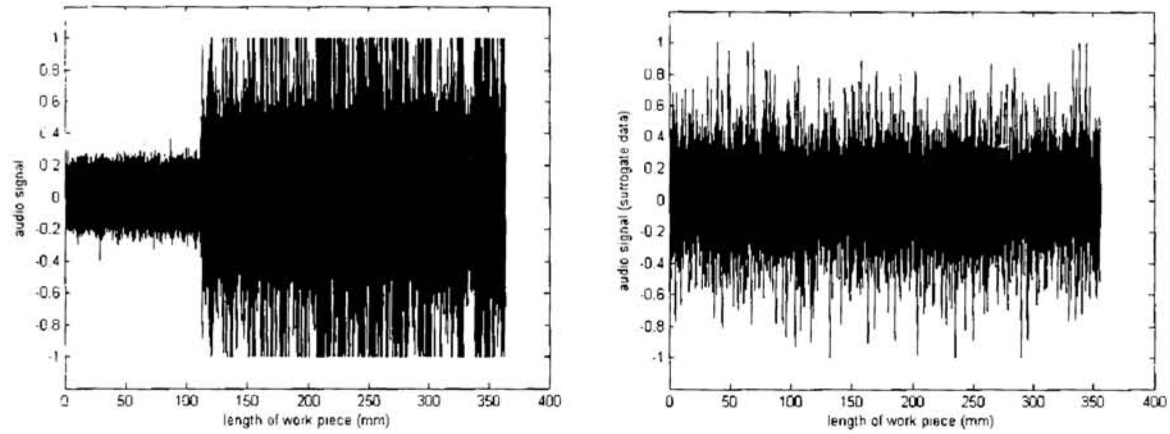


Fig. 5.10 Variation of optical roughness parameter R with respect to depth of cut from 0.3mm to 0.6mm

5.4 SURROGATE DATA TEST

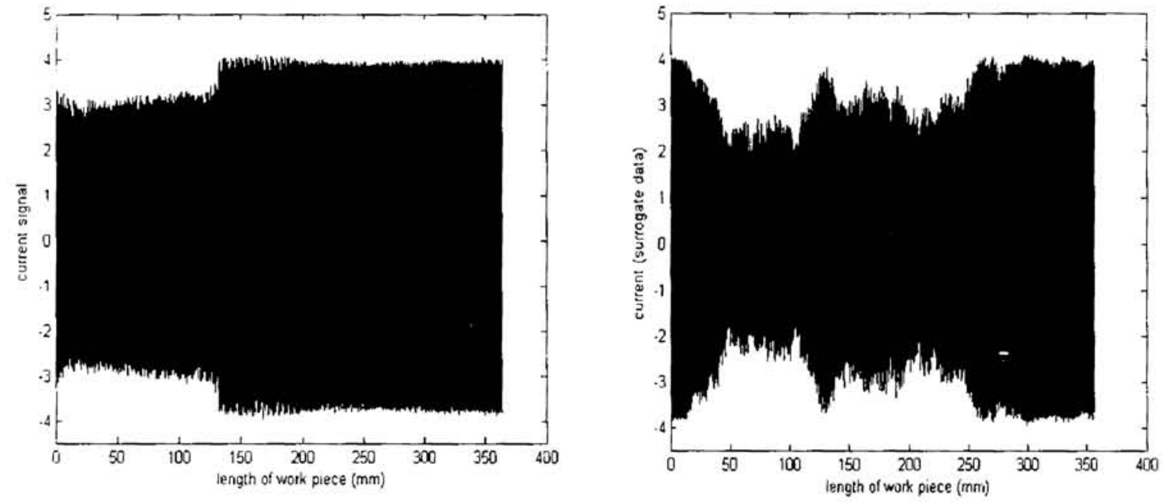
Before attempting any sophisticated nonlinear analysis of data from real world systems, one must ensure that the signal is truly nonlinear and not generated from any processes which are random uncorrelated or linearly correlated processes. One is expected to explicitly prove the nonlinear origin of the signal and thereby justify the use of nonlinear tools and models. The method of surrogate data testing [158] is proposed for this purpose and is widely used in several nonlinear time series analysis applications. The surrogate data technique is based on a hypothesis testing approach. To test the null hypothesis that there is no nonlinear structure in the data beyond the linearly correlated noise, a surrogate data set is generated which preserves the autocorrelation of the original time series and thus mimics only the linearly properties of the signal. This is done by Fourier transforming the original time series, randomly shuffling the phase of the transform with amplitudes left unchanged and then applying the inverse Fourier transform. If preservation of the amplitude distribution is also required, the amplitudes of the surrogate data can be rescaled to match the distribution of the original data or the histogram of the original data can be transformed to Gaussian prior to the fourier transform. The surrogate data set is compared with the original data using a discriminating statistic which is usually chosen to be one of the nonlinear measures from chaos theory.

Fig.5.11 (a) and (b) shows the original and the surrogate data obtained after randomization of the audio signal and Fig.5.12 (a) and (b) shows the original and the surrogate data for the current signal from machining process where the depth of cut is suddenly increased at a particular length of the work piece. Fig. 5.13 shows the evolution of PE for audio signal (a) original data (b) surrogate data of 5.11 (a) and (b). Fig. 5.14 shows the evolution of PE for spindle drive current signal (a) original data (b) surrogate data of 5.12 (a) and (b). The surrogate data is prepared using TISEAN [159].



(a) **(b)**

Fig 5.11 Audio signals (a) Original data (b) Surrogate data



(a) **(b)**

Fig 5.12 Current signals (a) Original data (b) Surrogate data

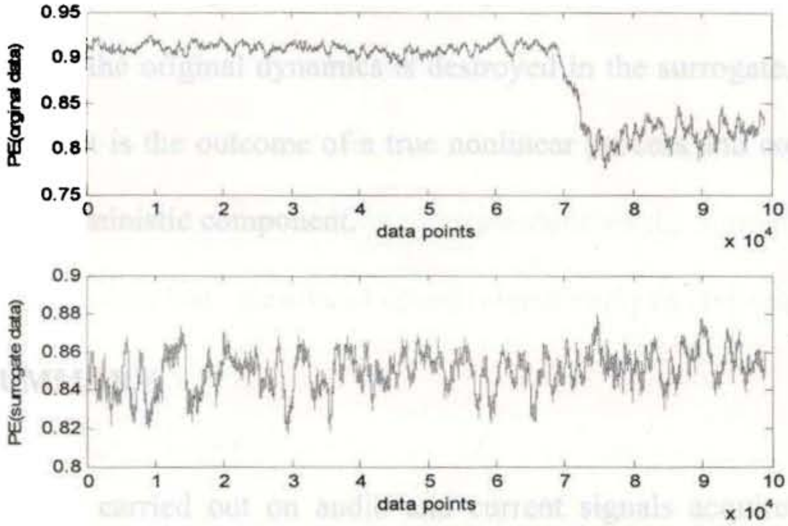


Fig 5.13 PE of audio signals (a) Original data (b) Surrogate data

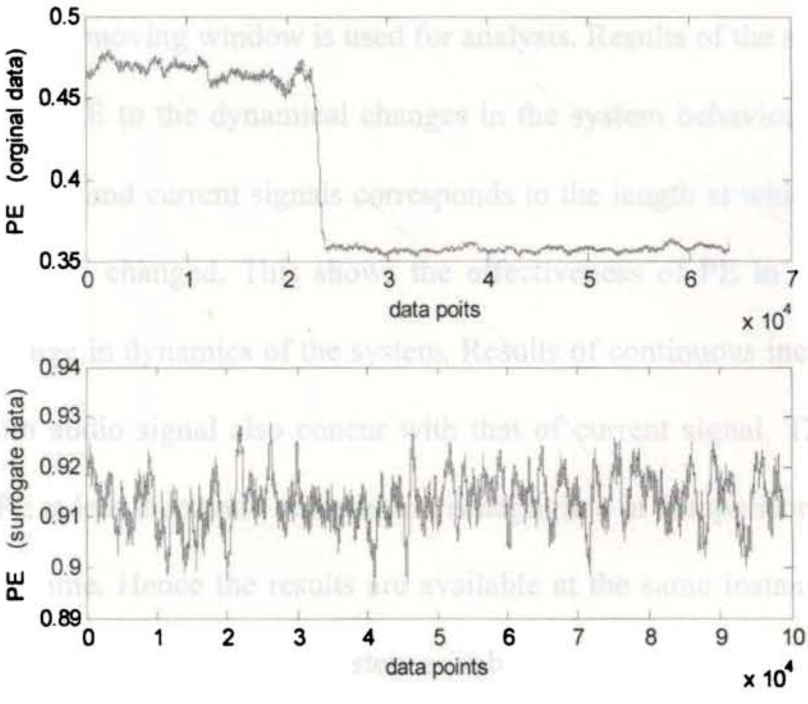


Fig 5.14 PE of current signals (a) Original data (b) Surrogate data

The PE values of surrogate data are entirely different from that of original data indicating that the original dynamics is destroyed in the surrogate. This suggests that the data set is the outcome of a true nonlinear process and contains a certain degree of deterministic component.

5.5 SUMMARY

PE analysis is carried out on audio and current signals acquired from turning process. Time series generated from the signals is divided in to non overlapping widows of 1024 samples and PE for every window is calculated. Variation of PE with respect to moving window is used for analysis. Results of the study reveal the sensitivity of PE to the dynamical changes in the system behaviour. The drop in PE from audio and current signals corresponds to the length at which the depth of cut is suddenly changed. This shows the effectiveness of PE in identifying the sudden change in dynamics of the system. Results of continuous increase in depth of cut from audio signal also concur with that of current signal. The calculation time for PE is less than nano seconds and is negligible in comparison with the data acquisition time. Hence the results are available at the same instant at which the data is acquired. This makes the system suitable for online application. The results are verified using existing measures of FFT and NCIR. It is observed that the time required to identify the change in dynamics is faster from audio signal than from current signal.

PE calculated from the mean gray level intensity histogram of the speckle pattern clearly shows the variation in surface texture due to increase in depth of cut. The results of PE analysis in this case are reinforced using the standard optical roughness parameter R. The nonlinear characteristic of the signals are established using surrogate data test. Results of speech signal analysis is discussed in the next chapter.

CHAPTER 6-RESULTS AND DISCUSSION ON SPEECH DYNAMICS

In this chapter PE analysis is carried out using speech signals in different normal and pathological conditions. Vocal sound signals corresponding to Malayalam alphabets from normal as well as abnormal subjects with vocal disorders are analysed. The results clearly distinguish the difference in dynamics between the two cases and the sensitiveness of PE to vocal disorders is established. The results are verified using standard FFT techniques. Maximal Lyapunov exponents are calculated to substantiate the results.

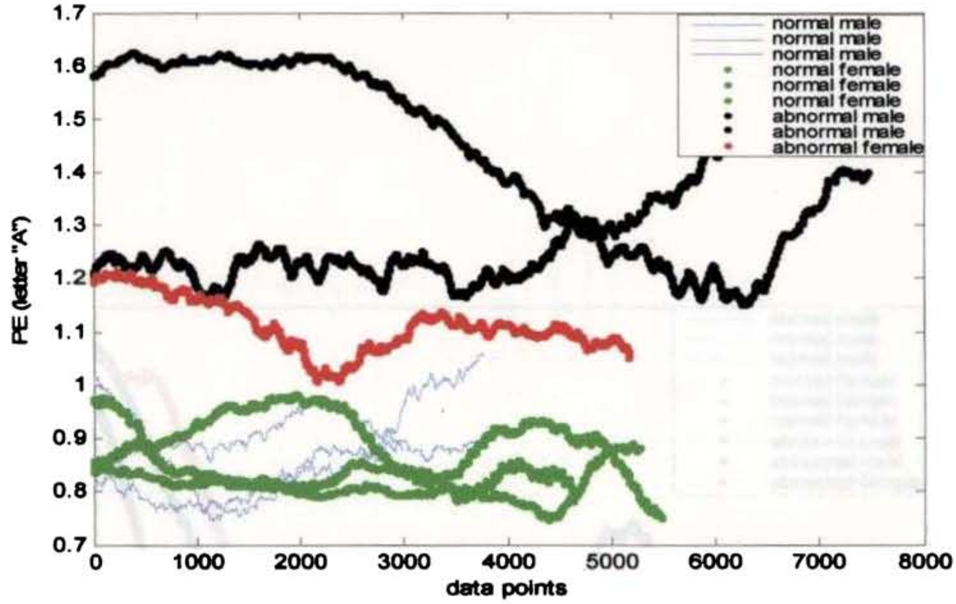
A range of invariant measures that show clearly the low dimensional nonlinear behaviour of individual vowel sounds are introduced in the recent years. The extracted feature from these signals is useful for study and investigation of vocal pathologies. Vocal sound signals are recorded from normal as well as abnormal subjects for different phonemes for PE analysis with an aim of charaterising normal and abnormal vocal sound signals.

6.1 SPEECH SIGNAL ANALYSIS

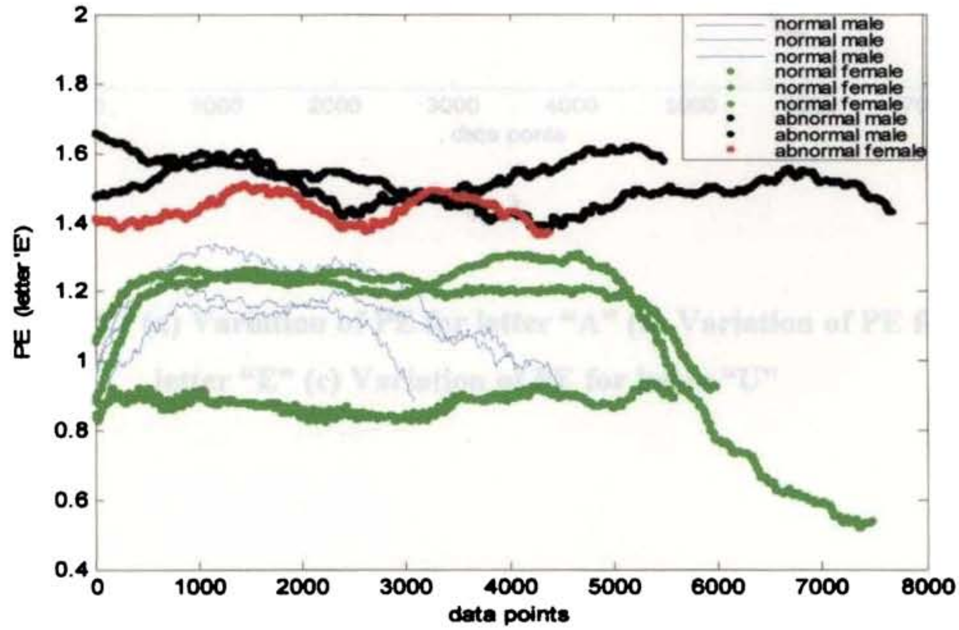
Effectiveness of PE to identify the vocal pathologies is verified on clinically characterized vocal sound data from patients suffering from three different cases. Vocal sound signals are recorded from 3 normal male subjects, 3 normal female subjects and 2 male and 1 female subjects with vocal disorder. The three cases of vocal disorders are of cancer, pollips and laryngitis. The audio signals are converted to digital time series by sampling it at a rate of 11KHz. These signals are then further analysed using PE for detailed study of qualitative difference in dynamics between normal speech signals and speech signals with disorder. Voiced speech signals of Malayalam viz. “A”, “E”, ”U ”, are recorded from each subject and the corresponding time series are subjected to PE analysis. The vocal cord vibrations corresponding to these phonemes are different while pronouncing it. PE of order 4 is calculated for moving non overlapping windows of 64 samples for each signal.

Fig.6.1 (a), 6.1(b) and 6.1(c) represents the variation of PE for letters "A","E","U" respectively. Normal female subjects are represented by green, normal male subjects are represented by blue, abnormal male represented by black and abnormal female represented by red. Results of the analysis clearly indicate that PE values of normal subjects are lower than that of abnormal cases. The results of the analysis indicate that irrespective of the gender as well as pathological condition PE values are higher for abnormal cases. This property of increased irregularity is identical for all the three sound signals. The higher values of PE of pathological subjects indicate that with abnormalities in voice signals, irregularities in speech signals increases. This reinforces the concept of presence of bifurcations leading to chaos in signals of vocal disorders.

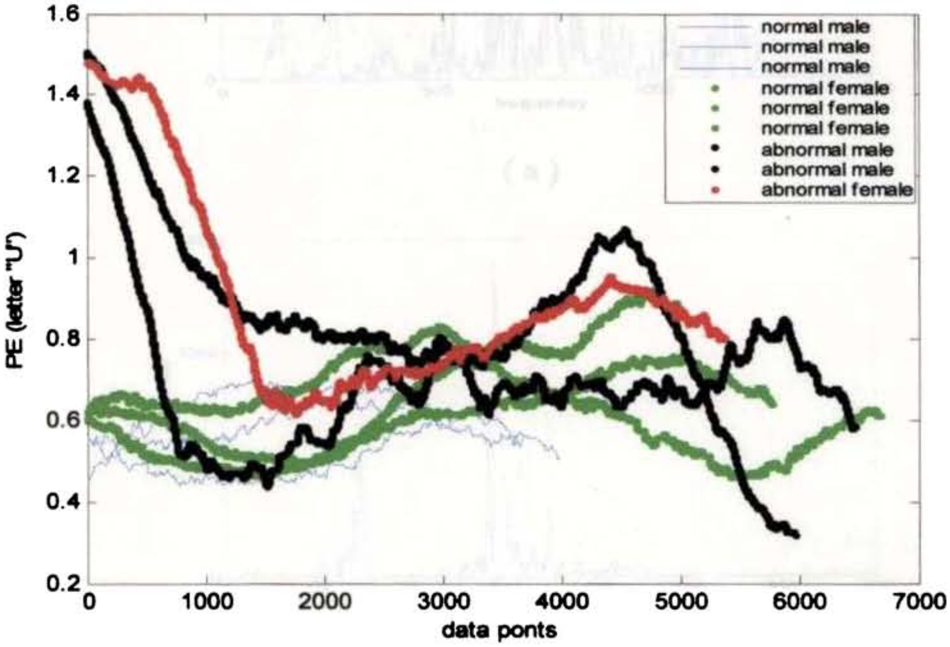
From these results it is clear that PE is effective in charaterising the amount of disorder in the vocal pathologies. This characteristic of PE can be made useful in the preliminary investigation of vocal disorders in clinical applications. This can be used as a tool by the clinicians during follow ups for identifying and evaluating the effect of any treatment given to the patients. At every level of treatment the PE data can be stored in the data bank of the patients and can be compared to the PE data before starting the treatment. This may also give first hand information in diagnosis about the level of disorder in pre and post treatment conditions. Hence it can be concluded that PE can be used as an indicator in deciding the final strategy of treatment in vocal pathological cases.


normal male
normal male
normal male
normal female
normal female
normal female
abnormal male
abnormal male
abnormal female
PE (letter "A")
data points

(a)

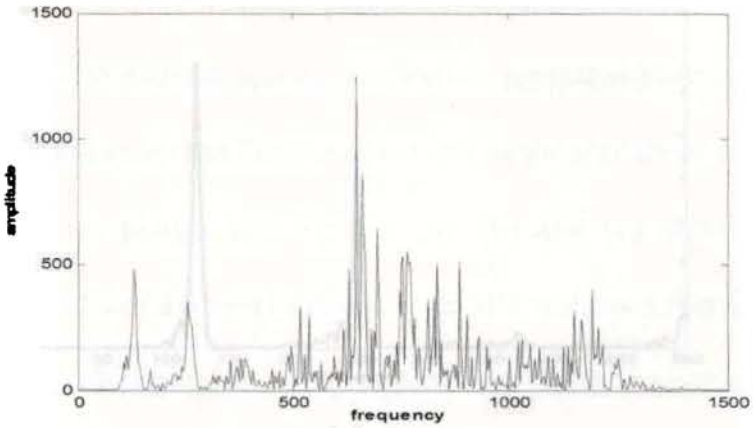

normal male
normal male
normal male
normal female
normal female
normal female
abnormal male
abnormal male
abnormal female
PE (letter 'E')
data points

(b)

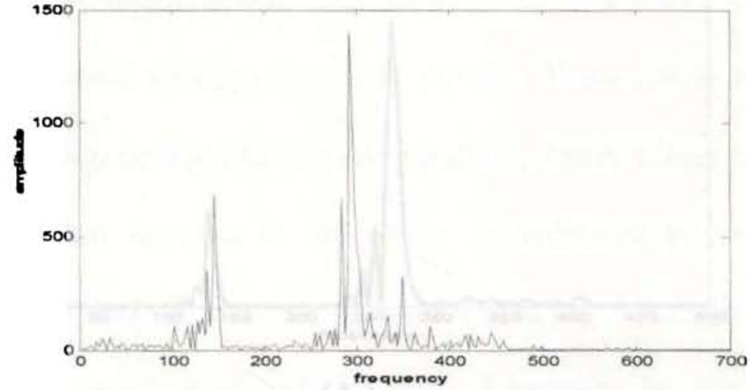


(c)

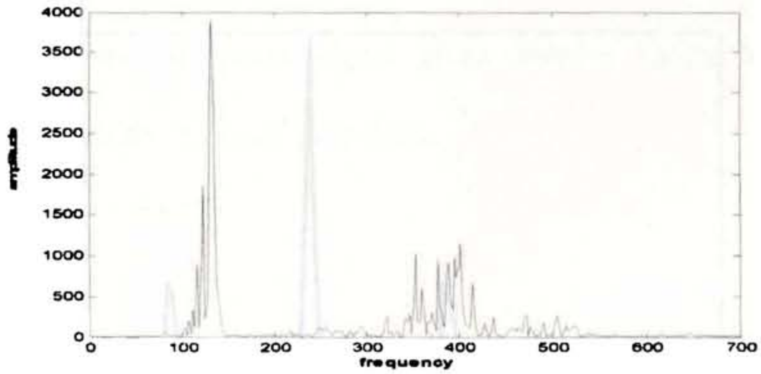
Fig 6.1 (a) Variation of PE for letter "A" (b) Variation of PE for letter "E" (c) Variation of PE for letter "U"



(a)

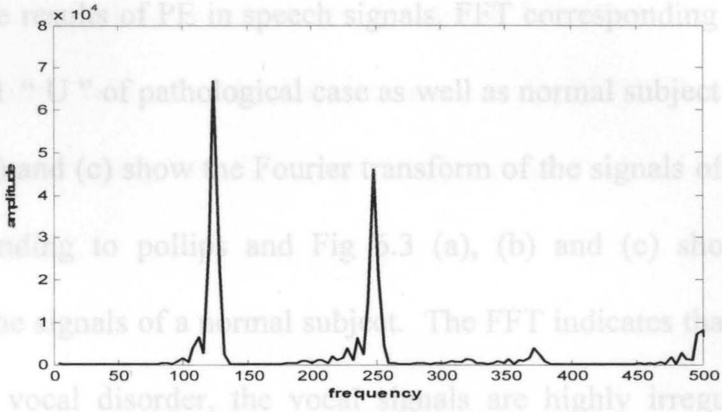


(b)

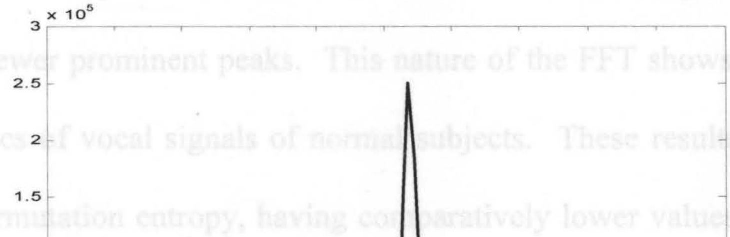


(c)

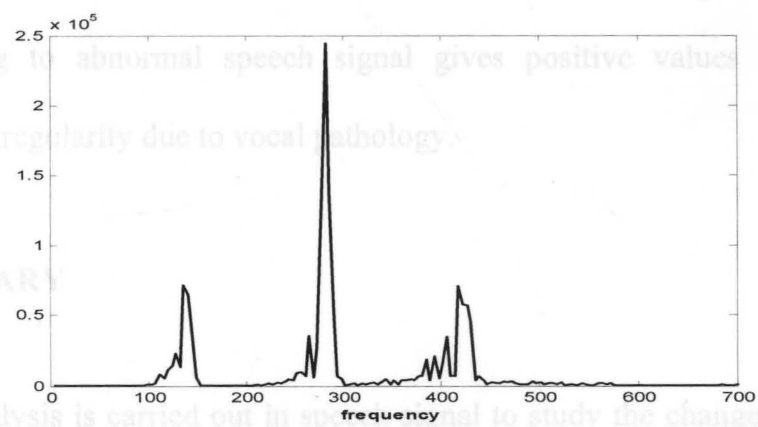
Fig 6.2 (a) FFT for letter "A" (b) FFT for letter "E"
(c) FFT for letter "U" for abnormal subject



(a)



(b)



(c)

Fig 6.3 (a) FFT for letter "A" (b) FFT for letter "E"

(c) FFT for letter "U" for normal subject

To confirm the results of PE in speech signals, FFT corresponding to three letters "A"," E", and " U " of pathological case as well as normal subject are calculated. Fig 6.2 (a), (b) and (c) show the Fourier transform of the signals of a pathological case corresponding to pollips and Fig 6.3 (a), (b) and (c) show the Fourier transform of the signals of a normal subject. The FFT indicates that in the case of subjects with vocal disorder, the vocal signals are highly irregular with large number of dominant peaks. In contrast, the FFT of normal subject shown in Fig 6.3 contains fewer prominent peaks. This nature of the FFT shows the regularity in the dynamics of vocal signals of normal subjects. These results reinforce the concept of permutation entropy, having comparatively lower values for dynamics with regular behavior. Increase in irregularity as indicated by rise in PE is confirmed by the presence of frequency components in Fig. 6.2(a), (b) and (c). In order to verify the results maximal Lyapunov Exponents for the signals are calculated using the software tool TISEAN [159]. The Lyapunov exponents corresponding to abnormal speech signal gives positive values which again confirm the irregularity due to vocal pathology.

6.2 SUMMARY

PE based analysis is carried out in speech signal to study the change in dynamics due to vocal disorders. Results show that PE for normal subjects are low compared to that of pathological cases where the dynamical behaviour is irregular. These results are verified using the standard linear method of FFT. Positive Lyapunov exponents corresponding to phonemes of abnormal subjects indicate chaotic behaviour.

CHAPTER 7- SUMMARY, CONCLUSIONS AND FUTURE DIRECTIONS

This thesis investigates the applicability of fast and robust technique of permutation entropy in detecting change in dynamics from real world systems: mechanical as well as biological. Turning process under mechanical systems and speech process under biological systems are considered for study and analysis. The work focuses on the effectiveness of PE in chatter detection in metal cutting and vocal disorder in speech signal. Traditional nonlinear methods fail to produce reliable results when the real world data is nonstationary and contaminated with noise. In an industrial set up it is necessary to detect the onset of chatter in such an early stage so that no chatter marks are made on the work piece and it does not get damaged. This requires a a fast detection algorithm which gives a clear measurement signal that includes features of chatter. Permutation entropy based methodology addresses the above issues and gives reliable results from experimental data. This is due to the fact that the machining process is nonlinear and PE algorithm is efficient in characterising the underlying dynamics from the time series of a suitable system variable.

PE analysis is carried out on audible sound signal and spindle drive current in turning processes on a lathe machine for sudden change in depth of cut and continuous increase in depth of cut on mild steel work pieces. During the machining process audio signal is captured using a unidirectional microphone and spindle drive current is acquired using current sensor. Microphone can effectively be used for chatter detection as the acoustic pressure during machining is proportional to the displacement of the tool. As the cutting force is related to the motor current, the current sensors are also effective in exploring the underlying dynamics of machining process.

Variation in surface texture from chatter free to chatter regime of the machined workpiece is analysed using PE of the speckle pattern acquired using speckle photographic method. The laser speckle pattern is recorded using Charge Coupled Device (CCD) camera and the gray level intensity histogram derived from it is used for further analysis of surface texture. PE of the mean calculated from the intensity histogram is found to be effective in revealing the change in surface texture produced by chatter vibrations.

Nonlinear methods of detection of voice disorder uses conventional methods based on state space reconstruction. This requires calculation of appropriate time lag and embedding dimension which restricts its application on real time basis. From the clinical point of view it is essential to have first hand information regarding the vocal disorder which will help in the choice of treatment strategy. Real time analysis of speech signal using PE can prove to be useful in this direction.

The results of PE analysis are confirmed using frequency spectrum and normalized coarse grained information rate. A direct consequence of chatter vibrations on dynamics is deterioration of surface finish of the work piece. This property of chatter dynamics is utilized to verify the chatter detection results. The change in surface texture in the chatter regime is confirmed by statistical parameter R.

PE analysis of audible sound signal and current 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. PE is effective in detecting the vocal disorders which establishes its suitability in the real time application of clinical diagnosis in this area.

7.1 THESIS SUMMARY

1) This work establishes that permutation entropy can be effectively used for the detection of change in dynamics in turning process using audio and current signals. The results are useful in detecting onset of chatter in turning.

2) The results reveal that the audio and current signals include features of chatter in turning process which in turn can effectively be extracted using the technique of permutation entropy.

3) The transition from chatter free to chatter regime is indicated by a sharp drop in PE value. PE values in the pre and post chatter regions are in the higher range compared to that around the chatter regime.

4) The chatter detection speed of PE from current signal with lower sampling rate is less compared with that of audio signal. As PE value is calculated for every 1024 samples, higher sampling rate results in faster detection of change in dynamics.

5) The results clearly indicate the change in surface texture due to onset of chatter. PE obtained from mean gray level intensity remains almost a constant with only slight variation in its value indicating regularity in the reflected light which in turn is indicative of a smooth surface for chatter free region.

6) The sudden increase of PE indicates an increase in irregularity thereby indicating an increase in surface roughness.

7) Variation of PE in the chatter region is much more compared to the chatter free region. This transition in dynamics is verified from the variation in waviness of the surface.

8) In case of vocal disorder, the increase in irregularity is reflected in PE values. The results of the analysis indicate that irrespective of the gender as well as pathological condition PE values are higher for abnormal cases.

9) The property of increased irregularity is identical for all the three abnormal sound signals. The higher values of PE of pathological subjects indicate that with abnormalities in voice signals, irregularities in speech signals increases.

7.2 CONCLUSIONS

1) PE algorithm is conceptually simple and computationally very fast and it gives reliable results from regular chaotic and real world data. It is robust against observational and dynamical noise, and non-stationarity in the signal. This makes PE an effective measure for experimental data sets where the signals are non-stationarity and contaminated with noise.

2) Time to calculate one PE value is less than a nanosecond. This time is negligible when compared with the data acquisition time. Hence PE values are available at the same instant at which the data is acquired. This feature makes it suitable for online application with suitable control mechanisms.

3) This technique is efficient in producing reliable results from small as well as large data sets. This feature is beneficial in cases where simultaneous data acquisition using different sensors are employed.

4) Microphone and current sensor are very easy to use and they are also very cheap in comparison to other sensors. They do not involve any positioning problem in the set up and are not affected by the geometry of cut. These factors are considerable in shop-floor applications.

7.3 CONTRIBUTIONS

1) Fast and efficient method of detection of onset of chatter in turning process from real time signals without preprocessing and fine tuning of data.

2) Easier method for detection of surface texture variation with onset of chatter.

3) Fast and robust technique for clinical diagnosis of vocal disorders.

7.4 FUTURE DIRECTIONS

1) Similar studies dealing with the effectiveness of PE for

- different sensors and signals
- different cutting processes
- different cutting conditions
- different work piece materials and

- high speed CNC machine

will help in extracting valuable information useful for practical applications.

2) Studies based on PE methodology can be carried out on different biological signals to understand the change in dynamics for various physical and mental states.
3) Surface texture analysis for different material under various cutting conditions can be evaluated.
4) Such studies can open avenues to possible application of PE analysis in online chatter control mechanisms.

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. The change in surface texture in the chatter regime is confirmed by statistical parameter R. 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 [160]. PE is effective in detecting the vocal disorders which establishes its suitability in the real time application of clinical diagnosis in this area.

International Journals

- Usha Nair, Bindu M. Krishna, V. N. N. Namboothiri, V. P. N. Nampoori. "Permutation Entropy Based Real Time Chatter Detection Using Audio Signal in Turning Process ", 2008, Advanced Manufacturing Technology. (under review)

- Usha Nair, Bindu M. Krishna, V. N. N. Namboothiri, V. P. N. Nampoori "Fast and Robust Technique for Chatter Detection Using Audio Signal in Metal Cutting", 2008, Mechanical systems and signal processing. (under review)

International Conferences

- Usha Nair, Bindu M. Krishna, V. N. N. Namboothiri, V. P. N. Nampoori "Permutation Entropy Based Speckle Analysis in Metal Cutting", 2008 Aug, SPIE Optical Engineering + Applications ,San Diego ,California, USA.

- Usha Nair, P.M Radhakrishnan V. N. N. Namboothiri "Fractal Extraction of Sound Signal in Machining", 2007 Jan, Joint Statistical Meeting and International Conference on Statistics, Probability and Related Areas, Cochin University of Science and Technology Cochin, Kerala, India.

- Praveen Cheriyan Ashok, Usha Nair, Varun K A S, V N N Namboothiri, V P N Nampoori "Speckle Metrology Based Study on the Effect of Chattering on Machined Surfaces", 2007 Aug, SPIE Optical Engineering + Applications ,San Diego ,California, USA.

- P.M Radhakrishnan, Usha Nair, V. N. N. Namboothir "Characterization of Speech Using Time Series Analysis" ,2007 Jan, Joint Statistical Meeting and International Conference on Statistics, Probability and Related Areas ,Cochin University of Science and Technology Cochin, Kerala, India.

- Rajesh V.G ,Usha Nair, V. N. N. Namboothiri,"Tool Condition Monitoring in Lathe Using Time Series Analysis", 2007 Jan, Joint Statistical Meeting and International Conference on Statistics, Probability and Related Areas, Cochin University of Science and Technology Cochin, Kerala, India.

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National Conferences

- Usha Nair " Nonlinear Analysis of Audible Sound Signal in Metal cutting Process", 2007 May, National Conference on electrical Systems and Control Technologies ,NIT, Calicut, Kerala, India.

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