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Defect detection of single point cutting tool using vibration signals and decision tree algorithm

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ABSTRACT

Tool wear and tool life are the principle areas are focus in any machining activity, the production rate, surface finish of the machined component and the service life of machine are directly related to the defects in the tool. Vibration signals and expert system like decision tree algorithm can be used to prevent the damage on cutting tools and work pieces when the defect in the tool arises. These studies have more relevant in manufacturing industries in order to match up with the competition. Based on the vibration signals and using expert system (decision tree algorithm), it is possible to find out the defects in the tool and different parameter which affects on the production rate. Decision tree algorithms are mostly used to study the structural health of the cutting tool. This method based on the analysis of defect detection in single point cutting tool using vibration signal which were obtained from the FFT and these tool vibration signals are used for obtaining various statistical features which indicates the various defects in the single point cutting tool. Condition monitoring is used for increasing machinery availability and performance, reducing consequential damage, increasing machine life, reducing spare parts inventories and reducing breakdown maintenance.

Keywords— **accelerometers, Decision tree algorithm, Defect detection, statistical features.**

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I. INTRODUCTION

Manufacturing industries presently got to cope up with growing demands for redoubled product quality, larger product variability, shorter product life-cycles, reduced price, and world competition. A key issue for an unattended and automatic machining system is that the development of reliable and strong observation systems. Machining issues, like cutter breakage, excessive wear, chatter and collision, impede production consistency and quality [1]. The complicated interactions between machines, tools, work piece, fluids, measurement systems, material, humans and the environment in cutting operations requires that sensors be employed to insure efficient production and protect workers and the environment. Loss due to disturbance could be prevented, or at least limited, using an in-process tool condition monitoring (TCM) system. An accurate and reliable TCM system could increase savings between 10% and 40% [2].

Tool wear monitoring methods can be classified into two categories: direct and indirect methods. Direct methods are based upon direct measurements of the tool wear using optical, radioactive, electrical resistance methods or vision systems, etc. These methods present the advantage of high accuracy but they have not yet proven to be very attractive either economically or technically. Indirect methods are based on the relationship between tool conditions and measurable signals from the cutting process. Different measurable signals have been used like force, vibration, acoustic emission, cutting temperature, etc. for detecting tool wear. Indirect methods are more suitable for continuous monitoring, whereas most of the direct systems are working intermittent. However, very few reliable indirect methods have been established forindustrial applications. This is mainly as a result of themonitoring

signals may be thought of random and non-stationary in nature, and since of the non-linear relationship between the measured features and tool wear.[1]In addition to these, there are various expert systems like principle component analysis, artificial neural network, strain measurement, fuzzy system, decision tree algorithm etc can be used to find out the damage on the cutting tool and work piece when the tool condition becomes faulty, these methods are helpful in finding the faults in the tool at the early stage, go a long way to diagnosis and correct those abnormalities before they become faulty.

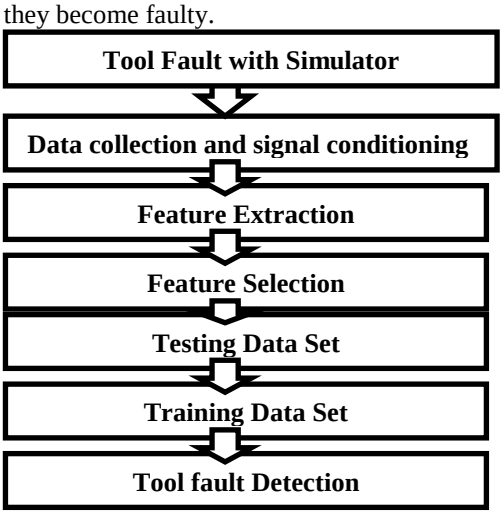

Fig.1 Process Block Diagram

Tool condition monitoring and diagnosis involves collection, processing and analysis of data related to the tool under various experimental conditions and interpreting theresults to the real life applications. A variety of techniques have been employed to carry out each phase of tool condition monitoring. Such phases include, choice of the parameters to be captured, feature extraction, feature selection and feature classification. Amongst the entire techniques decision tree algorithm is widely used for the defect detection of the single point cutting tool due to its simplicity and accuracy [1].

II. LITERATURE REVIEW

The various methods are used for the condition monitoring of the single point cutting tool. Along these methods now a days various expert system are used for the finding out the defects of the tool. A lot of research work is going on these methods, some of the research papers which I have reviewed are given below:-

M. Elangoven[1], study says that the tool wear and tool life are the important factor of any machining activity. The production rate, surface finish, machine condition are depends on the condition of the tool. He proposed that the use of experts system is most suitable for the online condition monitoring of the tool. He calculated the various statistical features using vibration signals of the tool which represents the leaves of the decision tree. He studied the expert systems (DTA & PCA) and concluded that the decision tree algorithm(DTA) gives the more classification accuracy than the principal component analysis. Decision tree algorithm (C4.5) is well suited for the fault detection for turning operation.

F. J. Alonso, D. R. Salgado[2], develop a reliable tool condition monitoring system(TCMS) for industrial application. They projected TCMS is predicated on the analysis of the structure of the tool vibration signals using singular spectrum analysis (SSA) and cluster analysis. SSA could be a novel non-parametric technique of time series Associate in time series analysis that decomposes the acquired tool vibration signals into an additive set of time series. They conclude that a number of the cluster element didn't carry info regarding the condition of the tool.

M. Elangovan, V. Sugumaran[3], studied the tool condition monitoring together with digital signal process may be used to stop damages on cutting tools and work pieces once the tool conditions become faulty. They also suggest that data processing approach is extensively used to probe into structural health of the tool and also the process. They discuss the condition monitoring of carbide tipped tool using Support Vector Machine (SVM) and compares the classification efficiency between C-SVC and m-SVC. And compare the result with the classifier like decision tree.

SanidhyaPainuli, M. Elangovan [4], on-line condition cost plays a significant role with reducing maintenance cost and increasing the production. This paper was an endeavour to assess capability and suitability of K-star classifier for tool condition monitoring. Vibration signals of single point cutting tool were acquired and statistical features were extracted. K-star classified extracted signals on basis of entropy. They conclude that the manual feature choice gave higher accuracy than dimensionality reduction algorithm.

N.Gangadhar, Hemantakumar, S. Narendranath [6], finding tool wear state in early stage with the assistance of monitoring system can reduces the downtime and excessive power. They get the vibration signals of the tool with the assistance of measuring system placed on the tool holder and simulated the worn tool for the fault diagnosis using machine learning technique for on-line tool condition monitoring. Statistical features are obtained from the vibration signal and also the vital features chosen from the J48 algorithm that conjointly work as a classifier. The many features were given input for the classifier and also the accuracy of the classification is examined.

C. Scheffer, P.S. Heyns [8],This paper represented the implementation of a TCMS on the shop floor, using NNs. it had been shown that the modelling technique proposed is very effective for estimating the flank wear of tool inserts using features derived from strain gauge measurements. Features representative of tool wear were generated from the static and dynamic parts of the force signals. The system was developed and tested in industrial surroundings, proving that such systems might run effectively below workplace conditions despite the various disturbances present. They conclude that the advantage of the system is its cost-effectiveness attributable to the utilization of straight forward sensors and electronics.

Weixiang Sun, Jin Chen [9],Vibration is the most helpful monitoring signal in engineering science which may well reflect the condition of a running machine; vibration is chosen because the monitoring signals during this paper. And eddy current sensors area unit accustomed collect radial vibration of the rotor. Six classical rotor running states as well as normal, unbalance, rotor radial rub, oil whirl, shaft crack and a simultaneous state of radial rub with unbalance are simulated on Bently Rotor Kit. And therefore the sample data are used to build fault diagnosis

test. C4.5 extracts information quickly from the training samples. Though C4.5 algorithmic program may be a good classifier and wide applied in several fields

.

III. EXPERIMENTAL SET UP

The experimental set up is shown in the Fig.2 which incorporates CNC machine, a piezoelectric accelerometer, a signal conditioning unit and a computer to record the vibration signals of the single point cutting tool (carbide insert). A shaft of mild steel of 32mm diameter was mounted in a chuck of CNC machine. And a single point cutting tool (carbide insert) was mounted in the tool post. The piezoelectric accelerometer was mounted on the tool holder using an adhesive technique (magnetic base). The accelerometer was directly connected to the signal conditioning unit, where the vibration signal goes through the analog to digital device (ADC) to the computer through an USB port. DEWE Soft v7.0.3 software package was used for recording the signals directly connected to the computer memory. The signal was recorded, then read and studied to extract different statistical features.

IV. EXPERIMENTAL PROCEDURE

Acquisition of the Vibration Signals:-

Acquisition of the vibration signals consist of the mounting a single point cutting tool in a tool holder and it was fixed on the tool post of the CNC machine. The piezoelectric accelerometer was fixed on the tool holder using adhesive technique (magnetic base) as shown in fig. the signal acquisition parameter like sampling frequency, sampling length, type of signal (amplitude in text format)was set on the FFT. The shaft of 32mm diameter was fixed on the chuck of the CNC machine. A rough turning was carried out to remove the top layer that undergoes the oxidation to smoothen out the top layer of the shaft. The various machining parameters like cutting feed, depth of cut, and spindle speed are set on the CNC machine. As the data acquisition system was start, the first few signals were ignored purposefully to avoid the initial vibration variation. As the process is stabilized required vibration signals were acquired. The vibrations acceleration signal plot for the various tool conditions, by keeping the same acquisition parameter are obtained for finding out the various statistical features.

Fig.2 Experimental set up for finding out the vibration signals for various condition of the tool.

Fault conditions of the single point cutting tool considered during the experimentation:-

1] Unused tool
2] Tool blunt low3] Tool blunt high
4] Tool tip loose

Machining parameter considered during the experimentation:-

Parameter	Values
Cutting feed	**0.15mm/s**
Depth of cut	**0.7mm**
Spindle speed	**500rpm**

The output of the experiment for the various tool conditions in the frequency domain are shown below. Fig.3 shows the vibration signals for the new tool condition. Fig.4 shows the vibration signals for the tool blunt low condition. Fig.5 shows the vibration signals for the tool blunt high condition. Fig.6 shows the vibration signals for the tool tip loose condition. These vibration signals are used to calculate statistical feature which represents the leaves of the decision tree. Each statistical feature contains the information about the condition of the tool.

V. DEFINITION OF STATISTICAL FEATURES

1] Standard deviation:

This is a measure of the power content of the vibration signal and indicates deterioration of the cutting tool. It is the root mean square (RMS) deviation of signal valuesfrom their arithmetic mean.

The following formula was used for computation of standard deviation.

$$\text{Standard deviation } (\sigma) = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left(\frac{X_i - \bar{X}}{s}\right)^3$$

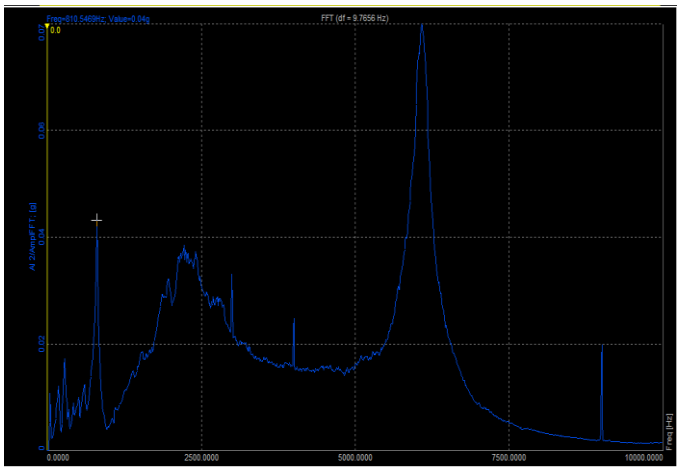

Fig.3 Frequency domain plot for new tool condition

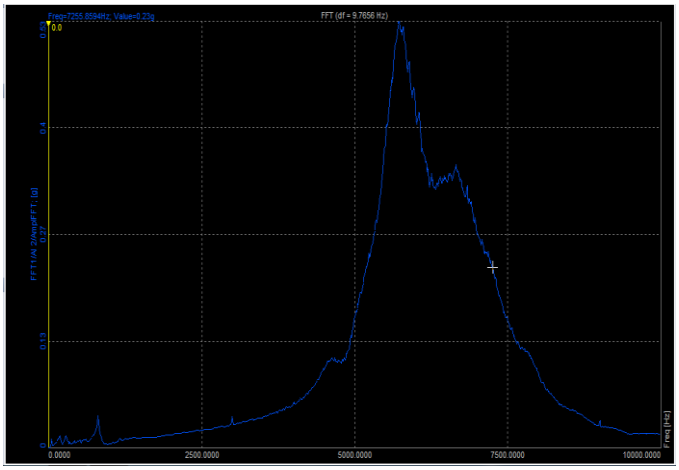

Fig.4Frequency domain plot fortool blunt low condition

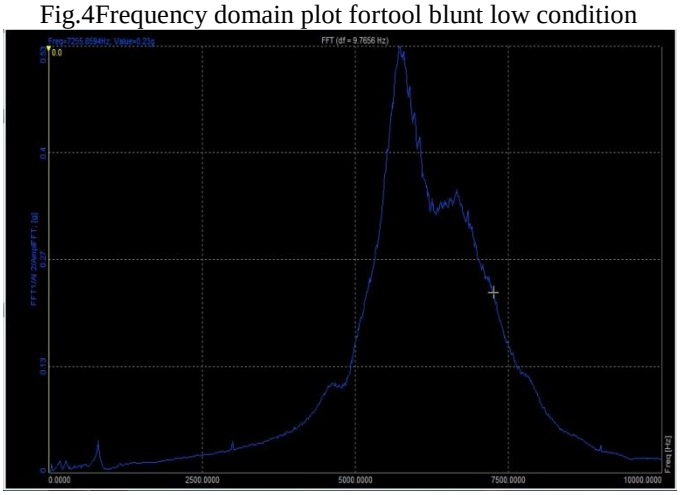

Fig.5Frequency domain plot fortool blunt high condition

2] Standard error:

The standard error of a statistic is the standard deviation of the sampling distribution of that statistic. Standard errors are important because they reflect how much sampling fluctuation a statistic will show.The standard error of a statistic depends on the sample size. In general, the larger the samples size the smaller the standard error.

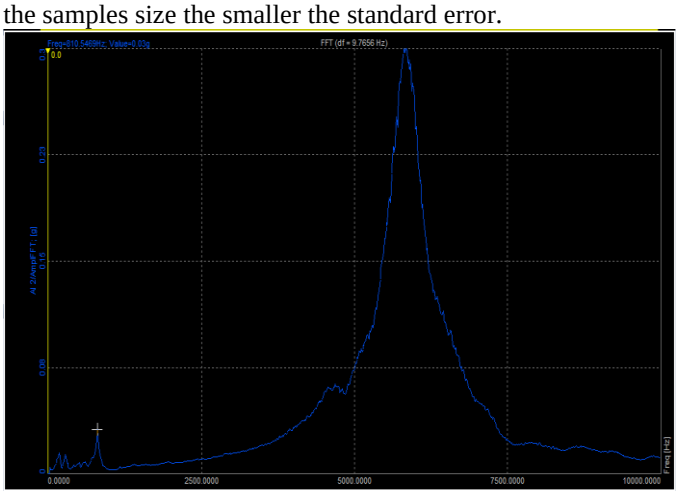

Fig.6 Frequency domain plot for tool tip loose condition

It is a measure of the content of error in the prediction of y for an individual x in the regression, where $\bar{X}$ and $\bar{Y}$ are the sample means and 'n' is the sample size.

Standard error of the predicted y= $\frac{\sigma}{\sqrt{N}}$

Where, N is number of samples.

3] Sample variance:

It is variance of the signal points and is given by the square of the Standard deviation.

Sample variance= σ^2 4] Kurtosis:

Kurtosis indicates the flatness or the spikiness of the signal. Its value is very low for good tool and high for broken or chipped off edge.

$$\text{Kurtosis}=\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum_{i=1}^{n}(\frac{X_i-\bar{X}}{s})^4\}-\frac{3(n-1)^2}{(n-2)(n-3)}$$

Where, *s* is the sample standard deviation.

5] Skewness:

Skewness characterizes the degree of asymmetry of a distribution around its mean. Positive skewness indicates a distribution with an asymmetric tail extending toward more positive values. Negative skewness indicates a distribution with an asymmetric tail extending towards more negative values. The measure of it is given by:

$$\text{Skewness}=\frac{n}{(n-1)(n-2)}\sum_{i=1}^{n}(\frac{X_i-\bar{X}}{s})^3$$

6] Range:

It refers to the signal values between the maximum and minimum for a given signal.

7] Minimum value:

It refers to the minimum signal point value of a given signal.

8] Maximum value:

It refers to the maximum signal point value of a given signal.

VI. DECISION TREE ALGORITHM (C4.5)

Decision tree represents the information in the signal as features, in the form of a tree. The classification is done through the decision tree with its leaves representing the different conditions of the tool. The sequential branching process ending up with the leaves here is based on conditional probabilities associated with individual features.

C4.5 algorithm introduced by Quinlan (1996) is one of thewidely used algorithms to generate decision tree. The decision tree induced with C4.5 algorithm plays a dual role in the present study namely, feature selection and feature classification. Prior to the presentation of the specific role of C4.5 algorithm, the underlying theory is presented. Decision tree algorithm (J48 – a WEKA implementation of C4.5) consists of two phases: building and pruning. The building phase is also known as 'growing phase'. Both these phases are briefly described in the following sub-sections.

1] Building the Decision Tree:

In the building phase, the training sample sets with discrete valued attributes are recursively partitioned until all the records in a partition have the same class. The tree has a single root node for the entire training set. A new node is added to the decision tree for every partition. For a set of samples in a partition S, a test attribute X is selected for further partitioning the set into S_1, S_2, S_3, . . .,S_L. For each new set S_1, S_2, S_3, . . .,$S_L$new nodes are created and these are added to the decision tree as children of the node for S. Further, the node for S is labelled with test X, and partitions S_1, S_2, S_3,. . ., $S_L$are recursively partitioned. When all the records in a

partition have identical class label, further portioning is stopped, and the leaf corresponding to it is labelled with the corresponding class. The construction of decision tree strongly depends on how a test attribute X is selected. C4.5 algorithm uses information entropy evaluation function as the selection criteria.

The entropy evaluation function is arrived at through the following steps.

Step 1: Calculate *Info (S)* to identify the class in the training set S.

$$Info(S) = -\sum_{i=1}^{k}\{[Freq(C_i, S/|s|)]\}$$

Where, $|S|$is the number of cases in the training set. C_i is a class, i= 1, 2, 3, . . ., K is the number of classes and freq$(C_i, S)$is the number of cases included in C_i.

Step 2: Calculate the expected information value, *infoX (S)*for test *X* to partition samples in *S*.

$$InfoX(S) = -\sum_{i=1}^{k}[(|S_i|/|S|\,Info(S_i))]$$

Where,*K* is the number of outputs for test *X*, S_i is a subset of S corresponding toi^{th} output and is the number of cases of subset S_i.

Step 3: Calculate the information gain.

$$Gain(X) = Info(S) - InfoX(s)$$

Step 4: Calculate the partition information value *Splitinfo (X)*acquiring for *S*, partitioned into *L*subsets.

$$Splitinfo(X) = -\frac{1}{2}\sum_{i=1}^{k}[\frac{|S_i|}{|S|}\log_2\frac{|S_i|}{|S|} + (1-\frac{|S_i|}{|S|})\log_2(1-\frac{|S_i|}{|S|})]$$

Step 5: Calculate the gain ratio

Gainratio(X)=Gain(X)-Splitinfo(X)

The *GainRatio(X)* compensates for the weak point of *Gain(X)*, which represents the quantity of information provided by X in the training set. Therefore, an attribute with the highest *GainRatio (X)* is taken as the root of the decision tree.

2] Pruning the Decision Tree:

It is observed that a training set in the sample space leads to adecision tree, which may be too large to be an accurate model; this is due to over-training or over-fitting. Such a fully-grown decision tree needs to be pruned by removing the less reliable branches to obtain better classification performance over the whole instance space even though it may induce a higher error over the training set. The C4.5 algorithm uses an error-based post-pruning strategy to deal with the issue of over-training. For each classification node, the C4.5 algorithm calculates predicted error rate based on the total aggregate of misclassifications at that particular node. The error- based pruning technique results in the replacement of vast sub-trees in the classification structure by singleton nodes or simple branch collections, if these actions contribute to a drop in the overall error rate of the root node.

Statistical features defined in Section V form the input to the algorithm. The features that appear at the nodes of the decision tree are in descending order of importance. Only features that contribute to the classification appear in the decision tree and others do not. Features that have less discriminating capability can be consciously discardedby fixing the threshold.

VII. CONCLUSIONS

The surface finish, dimensional accuracy, service life of the machine, production rate is mainly depends on the condition of the tool.Various Direct and Indirect methods are available for the conditioning monitoring of the tool. Indirect methods are more suitable for continuous monitoring, whereas most of the direct systems are working intermittent. However, very few reliable indirect methods have been established for industrial applications. Expert systems like decision tree algorithm (C4.5) is used for the condition monitoring of the tool which is based on the extracting the information about the condition of the tool from the vibrating signals. In this paper, expert system(Decision tree algorithm) is studied and found that the Decision tree algorithm is best suited for the conditioning monitoring of the single point cutting tool which gives the better feature extraction and classification accuracy than the other indirect methods.

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