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Fault Diagnosis of Single Point Cutting Tool through Vibration Signal using Decision Tree Algorithm

N. Gangadhar[a], Hemantha Kumar[a,*], S. Narendranath[a], V. Sugumaran[b]

[a]*Department of Mechnaical Engineering, National Institute of Technology Karanataka, Surathkal, Mangalore-575025, India*

[b]*VIT University, Chennai Campus, Vandalur-kelambakam road, Chennai-600048, India*

Abstract

Tool condition monitoring in machining plays a crucial role in modern manufacturing systems, finding tool wear state in early with the help of monitoring system will reduce downtime and excessive power drawing while machining. It increases machining quality as well as surface finish of machined components, reduces wear and tear of the machine and its components and hence increases machining efficiency. Vibration analysis of mechanical systems can be used to identify the tool condition to distinguish good and worn tool. This paper uses the vibration signals acquired using the accelerometer in a lathe with fresh and simulated worn tool for the fault diagnosis using machine learning techniques for online tool condition monitoring. Statistical features are obtained from vibration signal. Significant features were chosen from J48 algorithm, which is used as a classifier too. The significant features were given as input for the classifier and the accuracies of classification were examined. Results of (J48) algorithm were used to classify the condition of tool, also found its accuracy as of 89.38%.

Keywords: Condition monitoring; J48 algorithm; Accelerometer; Statistical features; machine learning technique.

1. Introduction

Manufacturing industry plays a major part over building economy in the underdeveloped as well as developing nations. Traditional metal cutting operations such as turning, milling, grinding etc. play an enormous role in production systems (Rehorn et al 2006). Machined quality, surface roughness and tolerances on finished products

*Corresponding author. Tel.: +918970375442.
E-mail address: hemantha76@gmail.com

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have direct influence of the condition of cutting tool and failure of cutting tool is the major cause of the unplanned interruption in a machining environment, which results in larger down time (Jantunen 2002). Numerical methods and analytical models are generally accepted for tool wear estimation with limited accuracy in comparison with modern online condition monitoring methods (Scheffer et al 2005). Li (2001) presented a state of art which reviews usage of Acoustic Emission (AE) method of cutting tool condition monitoring. Choi et al (1999) developed a real time tool condition monitoring system by combining AE method with measurement of cutting forces for turning operations. Jemielniak and Otman (1998) utilized statistical features such as kurtosis, skewness and root mean square (RMS) value from AE signals for finding monitoring tool wear. Dimla (2002) has shown that considerably less AE is produced while tool wear progresses in comparison with AE signal generated because of tool breakage and fracture. Lim (1995) illustrated the conditions of the cutting tool that can be detected from the corresponding vibration signatures acquired during machine turning operations. Taysir et al (1994) used ultrasonic method for online monitoring of tool wear. Abu-Zahra and Yu (2003) monitored the carbide tool wear in the lathe while turning by discrete wavelet transform of ultrasonic signals. In this investigation vibration signal is used to detect faults of single point cutting tool. Descriptive statistical features are obtained from vibration signal to serve the purpose of classification using machine learning approach.

2. Experimental studies

The details about the experimental setup and procedures are discussed in the following sections.

2.1 Experimental setup

The below Fig. 1 shows the experimental setup, which comprise lathe, a piezoelectric accelerometer, National Instruments (NI) data acquisition conjunction with the LabVIEW software with computer to acquire the signals. A workpiece of 25 mm diameter made up of mild steel was held in a four jaw chuck and High Speed Steel (HSS) cutting tool was firmly held in the tool post. Feed rate was set to 0.1 mm/s, cutting depth of 0.1 mm and rotational speed of 750 rpm was used as machining parameters. The kistler accelerometer (Type 8774A50) was mounted on the tool post using magnetic mount. The output from the accelerometer is collected using NI DAQ through Personal computer (PC). The output is viewed and analysed in LabVIEW Software the samples were read and the sampling rate were taken at 25 kHz. The signal was analysed and further processed to obtain various statistical features.

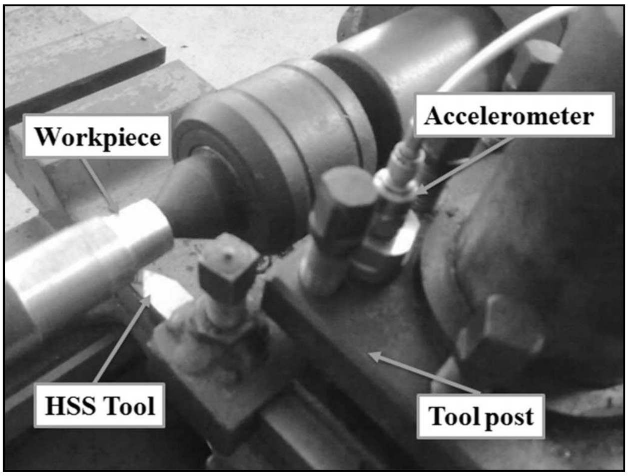

Fig. 1. Experimental setup

2.2 Experimental procedure

A healthy HSS tool was rigidly held on tool post and workpiece is clamped at four jaw chuck and few turning pass were carried to remove oxidized layers in workpiece and to remove any unevenness in workpiece and few minutes freely kept running to stabilize the machine vibrating parts at initial stage and initial few signals were not considered to avoid random vibration. The vibration signal was acquired for healthy tool along with simulated different faulty condition in tool made up of HSS material. The different simulated fault conditions presented in this analysis are:

1. Tool with low blunt
2. Tool with excessive blunt
3. Tool held loosely in the tool post.

Totally 160 samples were taken, where 40 samples were from the healthy condition and for each fault condition 40 samples were collected for 2 Sec time interval at 25kHz . Fig. 2 shows the time-domain signals for healthy and different simulated fault conditions.

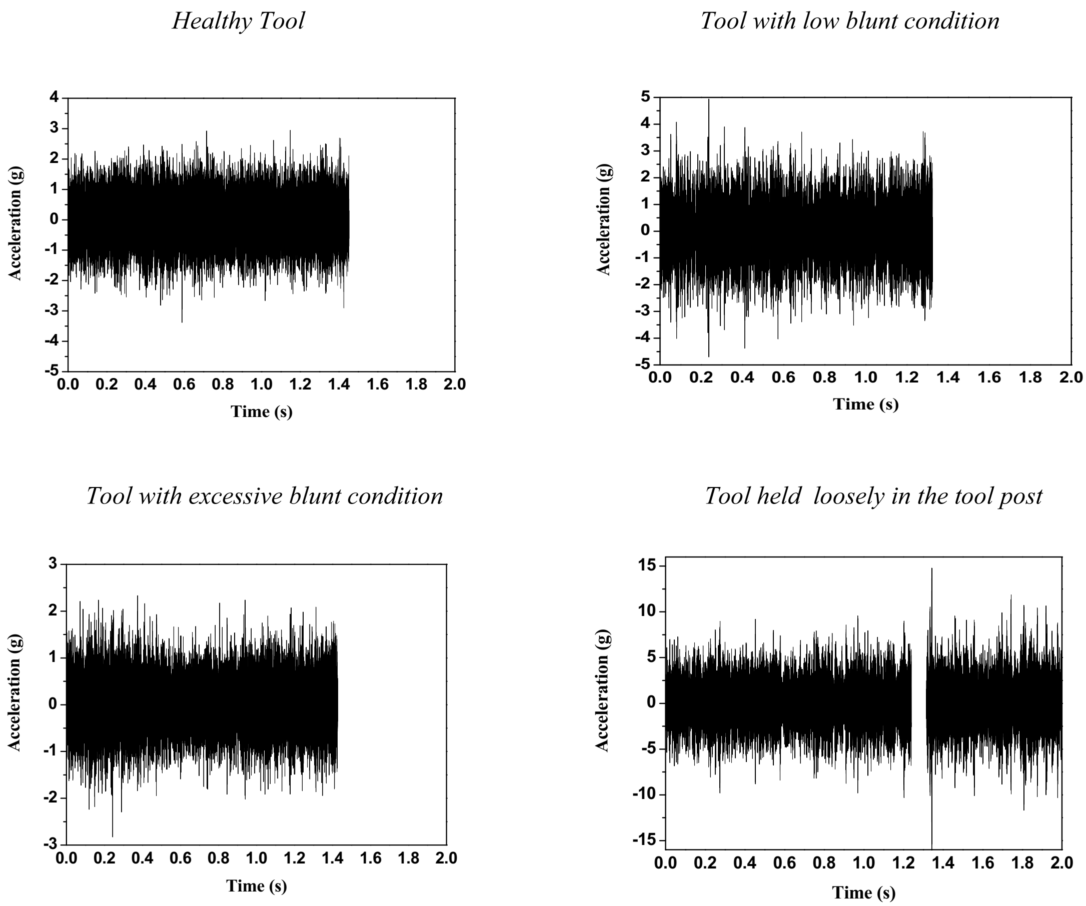

Fig. 2. Plots of time domain signal.

3. Statistical features extraction

From the obtained vibration signal, statistical features like mean, standard error, median, kurtosis, mode, sum, range, skewness, minimum and maximum, standard deviation are calculated and termed here 'statistical features' . Descriptions of computed features are explained below.

Standard error: It is the deviation involved to predict of *y* for an individual *x* in the regression, where *y* and *x* are the sample means and sample size denoted as *'n'*. The standard error of 'y' is computed as follows

$$Y = \sqrt{\frac{1}{n-2}\left[\Sigma(y-\bar{y})^2 - \frac{\left[\Sigma(x-\bar{x})(y-\bar{y})\right]^2}{(x-\bar{x})^2}\right]} \tag{1}$$

Standard deviation: It is a measure of dispersion of a set of data from its mean. It can be computed by using the following formula.

$$\sigma = \sqrt{\frac{\Sigma x^2-(\Sigma x)^2}{n(n-1)}} \tag{2}$$

Sample variance: It is the square of the standard deviation and it is computed using given below formula

$$\sigma^2 = \frac{\Sigma x^2-(\Sigma x)^2}{n(n-1)} \tag{3}$$

Kurtosis: It shows the spikiness or flatness in signals. In normal condition of the cutting tool its value is very low and in fault conditions of the tool because of the spiky behaviour of the signals its value is very high.

$$Kurtosis = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\Sigma\left(\frac{x_i-\bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{4}$$

Skewness: It characterizes measure of asymmetry of probability distribution about its mean. It can be computed by given below formula

$$Skewness = \frac{n}{n-1}\Sigma\left(\frac{x_i-\bar{x}}{s}\right)^3 \tag{5}$$

Range: It is the difference between minimum and maximum values for a given signal.

Minimum value: It is the value of minimum signal point for a given signal. When the tool gets worn-out, the vibration levels reach high. Thus, it can be utilized for monitoring tool wear status.

Maximum value: It is the value of maximum signal level for a given signal.

Sum: It refers to the values obtained by addition of points for every sample.

4. Decision tree

Decision tree is termed as a tree based knowledge methodology which represents rules for classification (Quinlan (1986), Sugumaran et al. (2007) and Shaktivel et al. (2010)). A standard *tree* generated with J48 algorithm comprises of one *root*, numerous *branches*, *nodes* and *leaves* (Fig.3). One branch consists of a bunch of *node* starting from *root* to *leaf*; and each node forms one feature. The *occurrence* of a feature in a decision tree gives the information related to the significance of the attribute related. The brief procedure involved in generation of Decision Tree and feature selection is given below:

- The set of features is treated as input for the algorithm and the corresponding output is a Decision Tree.
- It consists of leaf nodes, which indicate class labels, and the rest of the nodes related to the classes are being classified.
- The branches of the tree exhibit each predictive value of the generated feature node.
- Feature vectors are classified using decision tree, starting from root of the tree to node of the leaf.
- Each decision node in the tree, the most useful feature based on the estimation criteria most useful features can be chosen. The useful feature indemnified base on the criteria which invokes the concepts of information gain and entropy reduction are explained in subsection below.

4.1 Information Gain and Entropy Reduction

'Information gain' is the expected depletion in entropy due to portioning the samples according to given attribute, whereas *'Entropy'* characterizes the impurity of an arbitrary collection of examples. By adding information one reduces uncertainty. Information gain compares the entropies of original system and the system after information is added. Information gain (S, A) of a feature A relative to a accumulation of examples S, is defined equally:

$$Gain\ (S,A) = Entropy\ (S) - \sum_{v\in Value(A)} \frac{|S_v|}{|S|} Entropy(S_v) \tag{6}$$

Where, *Values (A)* is the group of all possible values for *A* attribute, corresponding S_v is the subset of *S* for which feature *A* has value *v*.

In the above equation the term *S* refers to entropy of the original collection and the next term is the expected value of the entropy. The expected entropy described by the term *A* is the direct sum of the entropies which belongs to each subset S_v. Therefore *Gain (S,A)* is the expected depletion in entropy due to known value of attribute *A*.
Entropy is given by

$$Entropy(S) = \sum_{i=1}^{c} -P_i \log_2 P_i \tag{7}$$

Where, c is the number of classes
P_i is the proportion of S belonging to class '*i*'.

5. Results and discussion

The statistical features discussed above are considered as features to serve as input for the algorithm. The corresponding condition or status of the categorised data will be the essential output of the J48 algorithm. The dataset is formed by input and corresponding output. The formed dataset is used to take the useful feature and classify using J48 algorithm the decision tree generated is shown in Fig. 3. The rectangle box in the decision tree indicates classes of the tool. Term within parenthesis, indicates two numbers separated by a slash. The first number (in case of two numbers) or the only number indicates the number of data points that assist the decision.

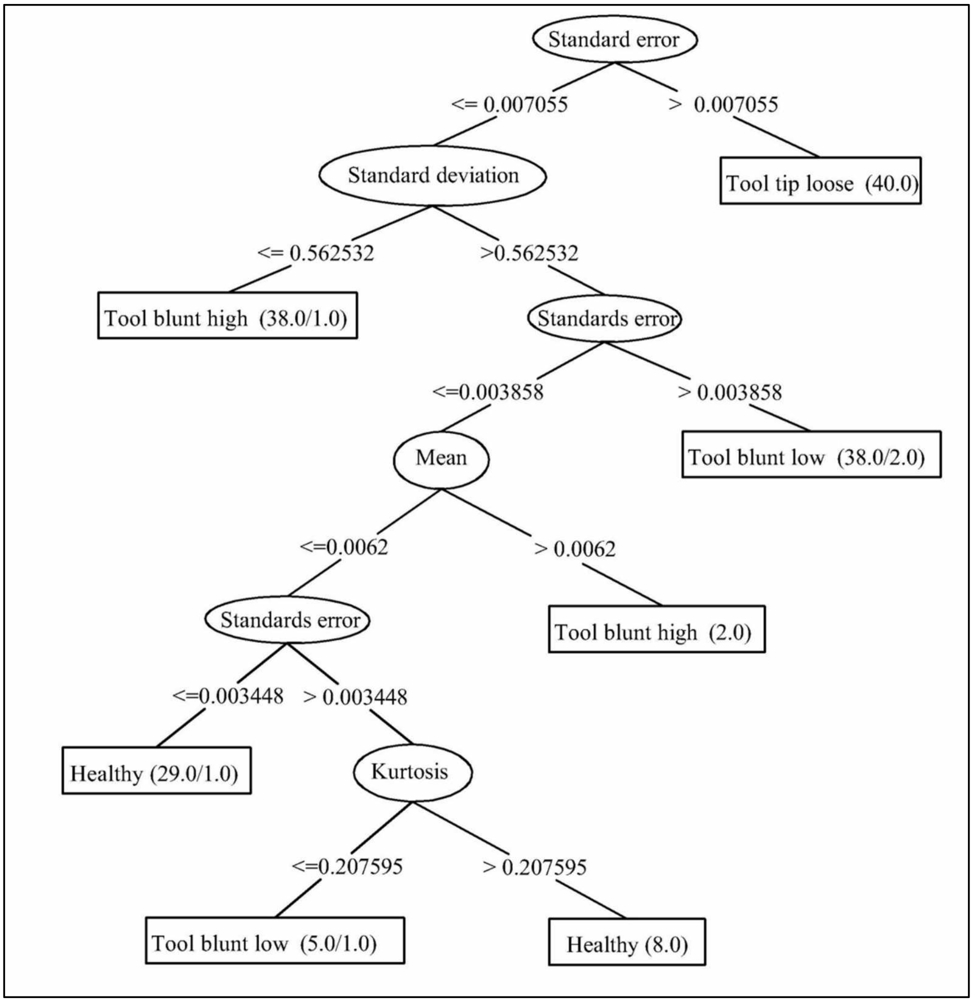

Fig. 3. Decision tree – Vibration Signals

5.1 Feature Extraction and Selection

From the obtained vibration signals twelve statistical features were taken out. Decision tree was employed to select significant features. In the decision tree, four significant features were selected namely Standard Error, Standard Deviation, mean and Kurtosis in the order of significance.

Classification accuracy of the J48 algorithm is presented in Table 1. The explanation of the confusion matrix is explained below:

- The number of correctly classified instances is shown in diagonal elements of the confusion matrix
- In first element of the first row indicates the number of samples that belongs to ‘healthy’ condition and classified correctly by the classifier as ‘healthy’.
- The second element of the first row represents the number of samples belongs to ‘healthy’ condition, but misclassified as tool tip loose it’s none
- The third element of the first row represents the number of ‘healthy’ samples misclassified as tool blunt low
- The fourth element of the first row represents the number of ‘healthy’ samples misclassified as tool blunt high and so on.

Table 1. Confusion matrix-Vibration signal

a	b	c	d	
32	0	7	1	a-Healthy
0	**40**	0	0	b-Tool tip loose
4	1	**35**	0	c-Tool blunt low
4	0	0	**36**	d-Tool blunt high

Table 2. Presents class-wise detailed accuracy. The term ‘TP rate’ stands for true positive value and for better classification accuracy it should be close to ‘1’. The ‘FP rate’ stands for false positive value and for better classification accuracy it should be close to ‘0’. From Table 2, one can realize the nearness of true positive value to ‘1’ and false positive value to ‘0’.

Table 2. Detailed accuracy by class

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.8	0.067	0.8	0.8	0.8	0.887	**Healthy**
1	0.008	0.976	1	0.988	0.996	**Tool tip loose**
0.875	0.058	0.833	0.875	0.854	0.929	**Tool blunt low**
0.9	0.008	0.973	0.9	0.935	0.969	**Tool blunt high**

The numbers of correctly classified instances are shown in diagonal elements of the confusion matrix. For example (Table 1.) in the first row, 32 samples are correctly classified as ‘Healthy’ where as 7 instances are misclassified as ‘Tool blunt low’ and 1 instance is misclassified classified as ‘Tool blunt high. Out of 160 samples 17 samples were wrongly classified by the J48 algorithm with a classification accuracy of 89.38 % for vibration signals.

6. Conclusions

Fault diagnosis of HSS cutting tool was investigated from vibration signal. Statistical features were classified from acquired vibration signals, J48 algorithm was used to understand and categorize the condition of the tool, found its accuracy as of 89.38%. Hence, J48 algorithm can be practically utilized to monitor the condition of HSS cutting tool.

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