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Fault Diagnosis of a Single Point Cutting Tool using Statistical Features by Random Forest Classifier

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Abstract

Objectives: There is a wide range of methods implemented for tool condition monitoring in the erstwhile manufacturing industry to ensure that the process continues uninterruptedly with minimal supervision. This monitoring method reduces the overall maintenance cost of machinery and prevents the occurrence of failure by prediction. This prior detection of tool wear, in turn, reduces the machine downtime and enhances machining efficiency. The progressive wear of a cutting tool can be detrimental to the quality of the machined surface, tolerances, dimensional accuracy and also adversely change the work or tool geometry. So the requirement of a diagnosing system with consistency is vital. **Method/Analysis:** This study deals with acquiring vibrational signals using accelerometer during turning operation performed on a lathe machine with good and fault simulated single point cutting tool. From the acquired signals, certain statistical features such as standard deviation, kurtosis etc. were extracted and substantial features were recognised using a decision tree algorithm. Those recognised features were deliberated in classifying data using random forest classifier. **Findings:** The accuracy of classification by the random forest classifier for all the signals combined together yields 74.4%. When considering feed rate and depth of cut as varying parameters yields an accuracy around 84%. Further an accuracy of around 88% was observed when considering depth of cut as varying parameter. When considering every experiment as a separate model yields around 95% classification accuracy. **Applications/Improvements:** This research work analysed the utilization of random forest classifier to identify the tool wear. It can be used in identifying the tool wear which affects surface finish, dimensional accuracy and tolerance of the part during machining. This work can be improved by analysing with different classifier algorithms to efficiently predict the tool wear.

Keywords: Confusion Matrix, Decision Tree, Feature Extraction, Random Forest, Statistical Features, Tool Condition Monitoring

1. Introduction

The current global scenario in the field of manufacturing is aimed at producing quality products at nominal prices. This advancement in the industrial scenario is being piloted by the ability to detect and predict the cutting tool wear, thereby increasing the productivity and also ensuring the quality, tolerance and surface finish of the product. To accomplish aforementioned, manufacturers are focusing on building a technique to achieve uninterrupted machining. Cutting tool condition monitoring is essential in automated manufacturing systems that have minimum human supervision, to prevent sudden failure or deterioration of the cutting tool. Flank wear is the most frequently witnessed tool wear in metal cutting operation and accompanied by adversaries such as error in dimensional accuracy, tolerances, and poor surface finish. Hence, this necessitates a detailed and thorough study of identifying the tool wear at an early stage.

Several attempts have been made by researchers and engineers to develop a condition monitoring system with high consistency. In[1] reviewed various works on researchers about condition monitoring using

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computational intelligence method to overcome machine downtime and maintenance cost due to equipment failures. In[2] reviewed various research works on flank wear prediction methods for monitoring the tool condition during turning process. In[3] used a laser doppler vibrometer to acquire online data from the boring operation to monitor the cutting tool condition. In[4] found that acoustic emission and cutting tool vibration can effectively respond to tool wear and surface roughness during turning operation. In[5] used nonlinear feature reduction and support vector regression for assessing the tool condition and predicting the useful tool life. In[6] used K-Star algorithm with statistical features in diagnosing the cutting tool state of turning operation. In[7] discussed the use of decision tree for feature selection from the extracted statistical features and classification with artificial neural network algorithm for high speed machining. In[8] found random forest classifier to be successful for identifying the sleep stage. In this paper, vibration signals obtained from the accelerometer set-up is used to investigate the condition of the single point cutting tool. Statistical features were obtained from the vibration signals. Features were reduced using decision tree and random forest classifier is used for the classification.

2. Experimental Arrangement

The experimental investigation was conducted in a lathe machine by performing the conventional turning operation. The Figure 1 and Figure 2 shows the experimental set-up comprising of anaccelerometer mounted on a single point cutting tool connected to a data acquisition device. A 25 mm diameter steel bar was used as the workpiece and machined using a brazed carbide tipped single point cutting tool. The vibration signals generated during the machining process was recorded using Dytran Uniaxial accelerometer which was mounted over the cutting tool with an adhesive. National Instruments USB Data Acquisition device NIVIB 4432 was attached to the accelerometer output which converted the analog signal output into a digital signal. The LABVIEW software from National Instruments was utilized in capturing the signal.

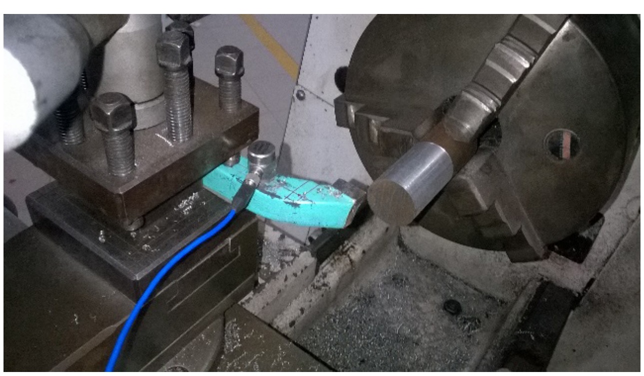

Figure 1. Experimental setup (accelerometer, cutting tool and specimen).

Table 1 displays the various machining parameters considered for the turning operation. The vibration signals were acquired for all possible combinations of the spindle speed, feed rate, and depth of cut with four different levels of flank wear.

2.1. Experimental Procedure

2.1.1. Acquisition of Baseline Signal

The Uniaxial accelerometer positioned over the single point cutting tool as shown in Figure 1. The peak frequency of the system was observed to be 6 kHz. According to the Nyquist sampling theorem, the sampling frequency of the system must be at least two times the observed peak

Figure 2. Experimental setup (data acquisition device and computer).

Table 1. Variable process parameters

Variables	Unit	Levels			
		1	2	3	4
Spindle speed	rpm	510	770	900	
Feed rate	mm/rev	0.109	0.122	0.135	
Depth of cut	mm	0.5	0.8	1.0	
Flank wear	mm	0	0.2	0.4	0.6

frequency of the system and hence the sampling frequency was taken to be 20 kHz.

The workpiece was firmly fixed in the chuck and in order to uniformly level the specimen surface and remove the oxide layers formed on the surface, rough turning operation was preliminarily performed. This was followed by uniform turning but the first few seconds after rough turning operation was neglected to avoid random variation in the signal. Acceleration signals were recorded sequentially using the data acquisition system after the turning operation was stabilized.

2.1.2. Fault Simulation

The flank wear was induced upon the cutting tool using a 'tool and cutter grinder' manually. Reference lines were drawn parallel to the tangent of the nose radius of the cutting tool and before incorporating the flank wear, the length between the topmost point of the nose radius and the reference line were noted. After the wear was manually induced, the length was measured again. The actual wear of the single point cutting tool is determined from the difference between the two readings.

2.1.3. Acquisition of Acceleration Signal

The vibrations generated during the machining operation was recorded by the accelerometer after the stabilisation of the turning operation. The experiment was performed by fixing the sampling frequency to 20 kHz and setting the sample length of the signal to 2000 points for all machining conditions. For various levels of tool wear the time domain plots are shown in Figure 3-Figure 6.

3. Feature Extraction

In data mining, feature extraction is performed on the initial set of measured data and derives features that are non-redundant and relatively more informative and useful. The extracted features comprise of more relevant information from the input data so that the classification can be done using the reduced data rather than the initial data set. The statistical features that were taken into account in this experiment are mean, median, mode, standard error, standard deviation, variance, kurtosis, skewness, maximum, minimum, range and sum. These features were extracted from the time domain of acceleration signals. The features that do not have the necessary information for the classification are neglected. The data reduction was

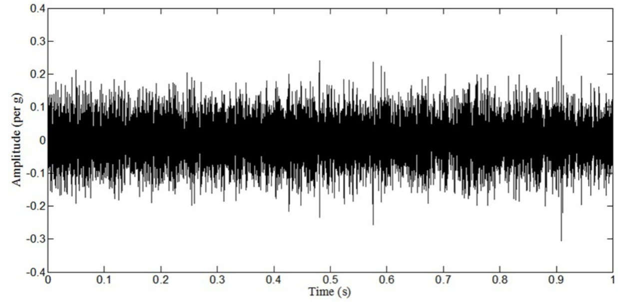

Figure 3. Time domain plot of good tool signal.

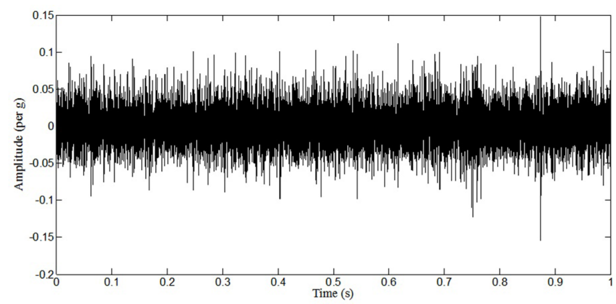

Figure 4. Time domain plot of 0.2 mm worn tool signal.

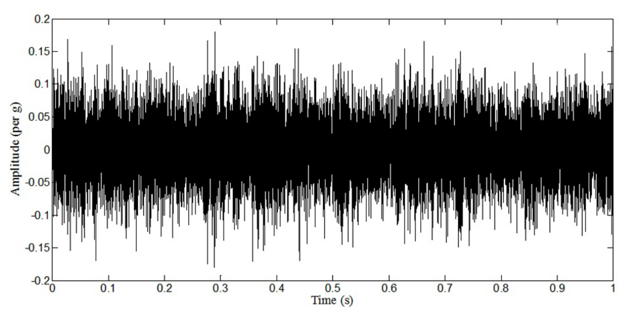

Figure 5. Time domain plot of 0.4 mm worn tool signal.

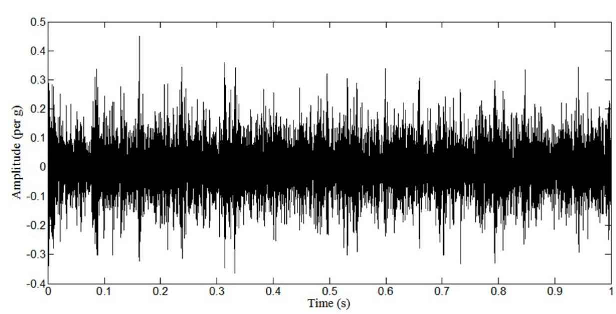

Figure 6. Time domain plot of 0.6 mm worn tool signal.

done through a decision tree classifier and the data classification through random forest tree classifier.

3.1. Feature Reduction using Decision Tree

All the twelve statistical features as input to the decision tree classifier reveals the importance of features in order. The significance of every feature is identified from their position in the decision tree. The feature at the uppermost position contains comparatively more information about the classification whereas the one at the lowermost level contains the least relevant information for classification. These features can be avoided and removed to improve the classification accuracy.

4. Description of Various Classifiers

4.1. Decision Tree

Decision tree, commonly used for data mining, builds a classification or regression models in the form of a tree structure. Typically, the tree consists of a single root and several branches, leaves and nodes. This tree structure enables the decomposition of a data set into smaller and smaller sub-sets while incrementally developing an association decision tree. It is capable of handling numerical as well as categorical data. The ultimate result is a tree with decision nodes and leaf nodes. The decision node comprises of two or more branches whereas the Leaf node denotes a decision or classification. At each node where a decision is made, the most substantial feature for classification can be determined based on an appropriate estimation criterion.

The criteria entailed in the selection of the most significant feature is pivoted around the concepts of information gain and entropy reduction. The decision tree is constructed from top to bottom from a root node, i.e. the topmost node with the best predictor and involves segregating the data into sub-sets that contain instances with similar values and thus are homogeneous. Entropy calculates the homogeneity of a data set with zero entropy indicating completely homogeneous and entropy as one signifying that the sample is equally and uniformly divided.

$$Entropy(s) = \sum_{i=1}^{n} -p_i \cdot log_2 p_i$$

Where p_i is the division of s belonging to class i and n is the number of classes.

On splitting a data set on an attribute, the decrease in entropy forms the basis for information gain. This information gain evaluates the variation in entropy before and after adding the information to the system. Information gain (s, x) of a feature relative to build up of instances s is given by:

$$Gain(s,x) = Entropy(s) - \sum_{v \in Value(x)} \frac{|s_v|}{|s|} Entropy(s_v)$$

Where $Value(x)$ is the collection of all possible values for attribute x and s_v is the subset of s for which feature x has a value of v.

$Entropy(s)$ in the equation signifies the entropy of the original collection s and $\sum_{v \in Value(x)} \frac{|s_v|}{|s|} Entropy(s_v)$ signifies the anticipated value of the entropy after s is divided using the feature x.

4.2. Random Forest Tree Classifier

Random forest is a collaborative approach for classification and regression by constructing a multitude of decision trees at the training time and outputting the class that is the mode of the classes of the individual tree, i.e. performing classification. The random forest begins with a standard machine learning technique, a decision tree in which a data is entered. As the data negotiates down this tree it gets allocated into smaller and smaller sub-sets. The result obtained is either an average or weighted average of all the terminal nodes that are negotiated. Greater inter-tree correlation is an indicative of greater random forest error rate and hence the trees should be as uncorrelated as possible.

Since, the predictions of a set of m trees are averaged in a forest by an individual weight function W_j, its predictions are:

$$\hat{y} = \frac{1}{m}\sum_{j=1}^{m}\sum_{i=1}^{n} W_j(x_i, x')y_i = \sum_{i=1}^{n}\left(\frac{1}{m}\sum_{j=1}^{m} W_j(x_i, x')\right)y_i$$

Thus, it is a weighted scheme with weights that average those of the individual trees. The neighbors of x' in this interpretation are the points which fall in the same leaf as x' in at least one tree of the forest. In this way, the neighborhood of x' depends in a complex way on the structure of the trees, and thus on the structure of the training set.

Random forest provides a relatively fast run time and has the ability to deal with unbalanced and missing data.

5. Results and Discussions

The systematic procedure performed to classify the condition of a single point cutting tool with random forest classifier is as follows:

- Decreasing the complexity of classification of data obtained from the vibration signals through the selection of significant features.
- Determining the classification accuracy of random forest classifier.
- Validation of the random forest classifier.

5.1. Feature Reduction

J48 decision tree classifier was used to remove the less contributing features for classification. A decision tree with 680 leaves with a classification accuracy of 71.11% was observed initially. After applying reduced error pruning on the same gave 72.86% classification accuracy with 186 leaves. By optimizing the minimum number of objects in the classification, the classification accuracy was found to be 72.31% with 34 leaves.

The effect of feature combinations in classification accuracy is displayed in Table 2. Those features which are not recorded in Table 2 does not hold sufficient information for classification. Hence, the less contributing features can be removed for future calculations. Thus, the computing effort utilized to classify the signal was reduced. From the graph shown in Figure 7, the maximum classification accuracy was noticed with five features. Those five features were taken for the further classification.

Table 2. Feature combination and their classification accuracy

No. of features	Features	Classification accuracy (%)
1	Standard deviation	64.34
2	Standard deviation + skewness	68.35
3	Standard deviation + skewness + variance	68.74
4	Standard deviation + skewness + variance + sum	72.07
5	Standard deviation + skewness + variance + sum + kurtosis	72.42
6	Standard deviation + skewness + variance + sum + kurtosis + range	72.21
7	Standard deviation + skewness + variance + sum + kurtosis + range + maximum	72.21

5.2. Classification Accuracy of Random Forest Tree Classifier

On merging the 108 experiment signals obtained from the turning operation performed on a lathe machine, the classification accuracy was observed to be 74.40% using random forest classifier.

The classification accuracy can be improved by reducing the complexity. By considering spindle speed as a separate factor, the maximum classification accuracy obtained is about 8% – 13% more than those obtained from the classification of all the signals combined as shown in Table 3. The comparison of the accuracies is shown in Figure 8.

To further enhance the accuracy level, the complexity is even more reduced by choosing the spindle speed and feed rate as separate factors wherein an increase of the classification accuracy by approximately 10% is observed. The classification accuracies are shown in Table 4. The comparison of the accuracies is shown in Figure 9.

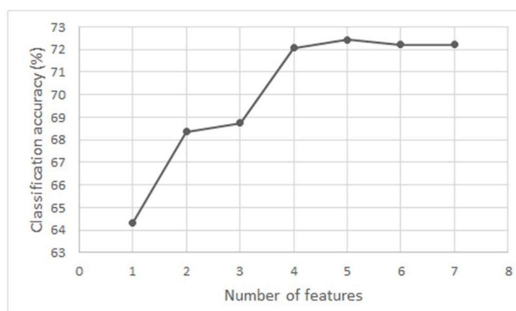

Figure 7. Number of features vs. classification accuracy.

Table 3. Classification accuracy of random forest classifier without considering feed rate and depth of cut as distinct factors

spindle speed (rpm)	Classification accuracy (%)
510	82.08
770	82.08
900	86.17

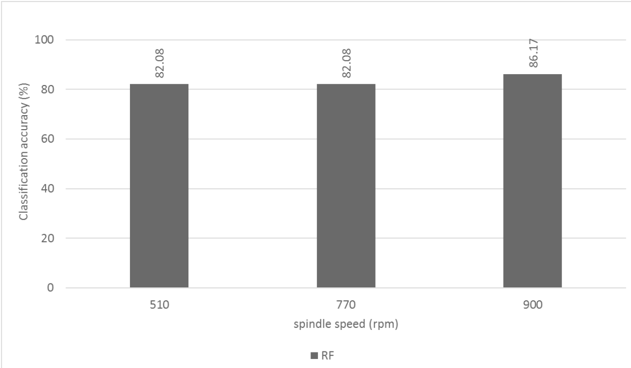

Figure 8. Classification accuracy comparison of random forest classifier without considering feed rate and depth of cut as distinct factors.

Table 4. Classification accuracy of random forest classifier without considering depth of cut as a separate factor

spindle speed *(rpm)*	Feed rate *(mm/rev)*	Classification accuracy *(%)*
510	0.109	89.92
510	0.122	86.00
510	0.135	85.25
770	0.109	86.58
770	0.122	92.08
770	0.135	83.08
900	0.109	83.50
900	0.122	88.25
900	0.135	92.50

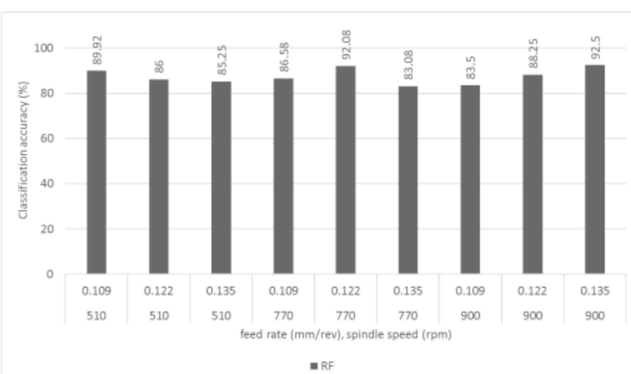

Figure 9. Classification accuracy comparison of random forest classifier without considering depth of cut as a separate factor.

Now, by considering spindle speed, feed rate and depth of cut individually as separate factors, an increment in the maximum classification accuracy by 5–8 % is observed. However, for certain combination of these factors the classification accuracy is lower than those obtained by considering spindle speed and feed rate as separate factors. The classification accuracies are shown in Table 5. The comparison of the accuracies is shown in Figure 10.

Table 5. Classification accuracy of random forest classifier considering depth of cut, feed rate and spindle speed as distinct factors

spindle speed *(rpm)*	Feed rate *(mm/rev)*	Depth of cut *(mm)*	Classification accuracy *(%)*
510	0.109	0.5	98.75
510	0.109	0.8	97.50
510	0.109	1	97.25
510	0.122	0.5	96.75
510	0.122	0.8	92.00
510	0.122	1	89.50
510	0.135	0.5	92.75
510	0.135	0.8	89.50
510	0.135	1	98.00
770	0.109	0.5	84.50
770	0.109	0.8	100.00
770	0.109	1	90.25
770	0.122	0.5	97.25
770	0.122	0.8	99.00
770	0.122	1	99.50
770	0.135	0.5	83.00
770	0.135	0.8	93.00
770	0.135	1	92.25
900	0.109	0.5	87.25
900	0.109	0.8	92.50
900	0.109	1	98.50
900	0.122	0.5	92.50
900	0.122	0.8	98.25
900	0.122	1	98.00
900	0.135	0.5	98.50
900	0.135	0.8	93.50
900	0.135	1	99.00

From the data obtained through classification using random forest classifier, it is seen that the classification accuracy generally has an increasing trend if separate models are considered. Hence, using random forest classifier would be convenient for monitoring and classifying the tool condition for a variety of spindle speed, feed rate and depth of cut as it provides 74.40% classification accuracy for all the signals combined.

5.3. Classifier Validation

The confusion matrix obtained upon performing the classification process is depicted to validate the choice of random forest classifier. The confusion matrix shown in Figure 11 contains a series of rows and columns denoting the different tool wear conditions. In the confusion matrix shown in Figure 11, the first element in the first row indicates the number of signals belonging to the good condition of the tool classified as GOOD. The second element in the first row signifies the number of signals that are of good condition and characterized as 0.2 mm flank wear (FLW1). Similarly, the third and fourth element in the first row signifies the number of signals belonging to good condition but characterized as 0.4 mm (FLW2) and 0.6 mm (FLW3)

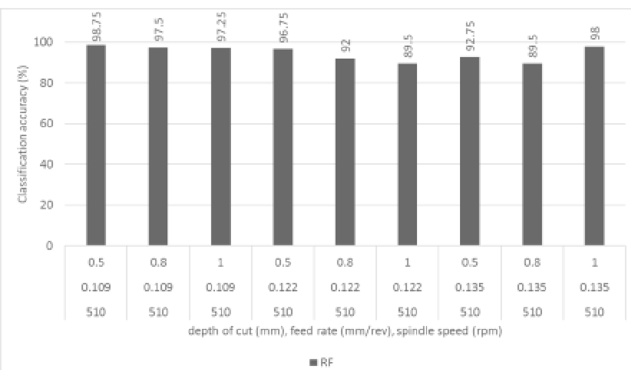

Figure 10. Classification accuracy comparison of random forest classifier considering depth of cut, feed rate and spindle speed as distinct factors.

GOOD	FLW1	FLW2	FLW3	< classified as
2093	1	360	246	GOOD
7	2398	131	164	FLW1
296	182	1797	425	FLW2
331	153	469	1747	FLW3

Figure 11. Confusion matrix of random forest classifier for all signals combined.

respectively. This same pattern can be followed to interpret all other elements in the confusion matrix. Hence, it can be deduced that the diagonal elements of a confusion matrix are the correctly classified instances and the off-diagonal elements are incorrectly classified instances.

From this confusion matrix, the misclassification of tools in GOOD condition as FLW2 and FLW3 may be because the signals observed for some machining parameters are same for FLW2 and FLW3. Also, similar misclassification is observed between FLW3 and FLW2 conditions due to the resemblance of signals recorded in those two cases that may have been caused by a likeliness in the tool tip cutting edge.

6. Conclusion

This study highlights the use of random forest classifier as an effective tool for monitoring the condition of a single point cutting tool. The statistical features were extracted from the time domain signals and the necessary features to classify efficiently were selected using J48 decision tree algorithm. This feature reduction significantly reduced the computing time and effort required. For all signals combined, the random forest classifier provided a classification accuracy of 74.40% and hence is suitable for all spindle speed, feed rate and depth of cut. Moreover, classification accuracy of nearly 98% is obtained when spindle speed, depth of cut and feed rate are considered separately. When considering spindle speed and feed rate separately yields around 84% classification accuracy.

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