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Milling cutter condition monitoring using machine learning approach

A D Patange[1*], Jegadeeshwaran R[1] and N C Dhobale[1]

[1]School of Mechanical and Building Sciences, VIT University, Chennai, Tamil Nadu, India
Email: abhipatange93@gmail.com

Abstract. The cutting tool condition drives the economy of machining processes in manufacturing industry. The failures in cutting tool are unbearable and affect the drive of machine tool which reduces life. Hence it necessitates reducing power consumption using monitoring cutting tool condition and hence requires an efficient supervision to monitor and predict faults. Simply stated, the condition which curtails cutting tool life highlighted before it turns into a tool wear, breakage and failure. This ensures optimized and effective use of a cutting tool, saves maintenance/repair time, enhances constancy in a process etc. The recent development in Machine Learning (ML) and its applicability for condition monitoring approach has drawn attention of researchers. Machine learning examines existing and past indications to predict conditions in future. This paper presents machine learning based condition monitoring of milling cutter of vertical machining centre (VMC). The vibration signals acquisition of 4 insert milling cutter is carried out with healthy and various fault conditions. The Visual Basic (VB) code and script is used to extract statistical features and decision tree algorithm is used to select relevant features. The different conditions of milling cutter are classified using tree family classifiers. The effort made in this work is to check applicability of ML approach for milling cutter fault diagnosis for reducing power consumption of drive of machine tool.

1. Introduction

The health monitoring of cutting tool is inspired and originated due to necessity of developing unmanned machining systems which are self-sustained and intelligent [1,2]. One of the most important monitoring requirements in an unmanned manufacturing system is in-process detection of tool breakages and execution of prompt action [3]. This has evolved the need of 'Tool condition monitoring' or 'Health monitoring of tool' in past several years. The tool condition monitoring methodologies are usually classified into two broad types such as 'Offline/Direct methods' and 'Online/Indirect methods'. The direct methods are mostly appropriate for inspecting and analysing of complex failures (hard faults) which usually are unpredictable and hence found unsuitable for machine learning domain [4]. On the other hand indirect methods are based most appropriate method for monitoring soft faults which evolve gradually with respect to time leading to continuous deterioration of the tool [5]. The recent development in Machine Learning (ML) and its applicability for condition monitoring approach has drawn attention of researchers. Machine learning examines existing and past indications to predict conditions in future [6]. In this paper, the vibration signals acquisition of 4 insert milling cutter is carried out with healthy and various fault conditions. The Visual Basic (VB) code and script is used to extract statistical features and decision tree algorithm is used to select relevant features. The different conditions of milling cutter are classified using tree family classifiers i.e. J48, Logistic Model Tree and Random Forest algorithms.

2. Literature review

The research related to tool condition monitoring through machine learning approach is presented here to highlight the research gap. This research is specifically confined to the study of vibration involved in machining and its relation with cutting tool condition. Vibration monitoring is useful to identify primary symptoms about tool condition, dimensional variations and surface roughness in machining applications than others. The customized regulation of vibrations for corresponding removal rate and avoidance of tool breakage at the shank, in process tool breakage, wear and chatter recognition is a vital task [7]. It is recommended that vibration signals are more sensitive, robust, reliable, requires less accompanying instrumentation and can be employed for real time application [8]. The cutting forces change dynamically for cutter exit which leads to vibration especially when forces change their directions due to the variation of dynamic chip thickness [9]. In the experiment carried by [10] it is observed that if nose wear is greater than 0.2 mm lead to the possibility of cataclysmic breakdown. Moreover he found that the notch wear conversely rose progressively in the beginning of machining, and continued to be unchanged for the rest tool life. Second step, these signals are extracted as pertinent features using statistical, wavelet or histogram approaches etc. In the comparison of seven statistical features amongst which root mean square found most significant [11]. In the statistical analysis of acquired signals using I-kaz technique where correlation of I-kaz coefficients and Z^∞ values with resultant flank wear width data were presented. It has been observed that Z^∞ values reduce when VB rises and reduces when machining speed rises [12]. In experimentation of [13] obtained classification accuracy of 72% with thirteen extracted features. But when only standard error, standard deviation, variance, kurtosis and mode were selected accuracy increased to 76.9%. In the comparison of both histogram and statistical features, it is demonstrated that classification accuracy of 86.34% is found when statistical approach is used than histogram (73.61%) i.e. statistical technique extracts features more accurately than histogram technique [14]. The J48 algorithm was utilised for selecting features based on the information gain of the features which helps in reduction of domain knowledge [15]. Lastly, the fault diagnosis of tool condition is accomplished by analysing extracted features applying machine learning techniques. The features classification carried using clonal selection classification algorithm by analysing diverse population with high fitness antibodies instead of a single antibody solution [16]. When Naïve Bayes and Bayes Net classifiers was used and found accuracy of 85.28% and 86.34% respectively [14,17]. It is found that the use of statistical technique for feature extraction is most favourable as compared to others. The decision trees are suitable for feature selection as it reduces dimensionality. It is also found that use of tree family classifiers for tool condition monitoring is not reported till now.

3. Experimental study

The experimentation for signal acquisition was conducted on Vertical Machining Centre (VTEC Model CCS00605) in Axis Metalcut Technologies, Bhosari-Pune.
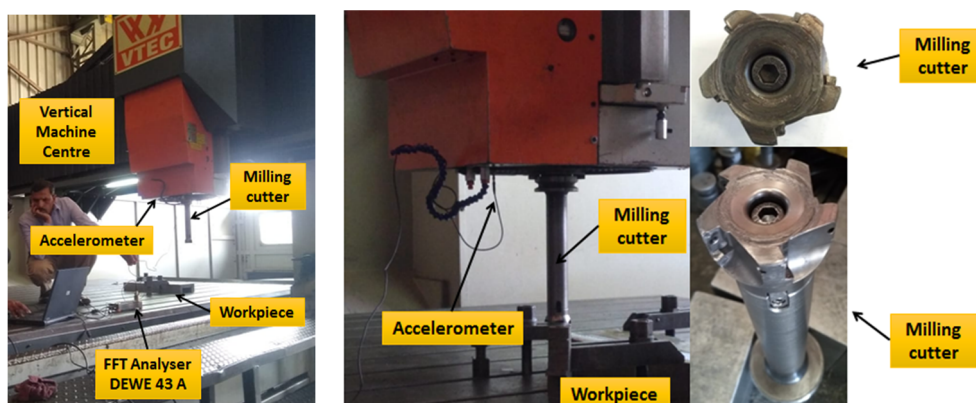

Figure 1. Experimental setup

Figure 1 shows the experimental setup. The piezoelectric accelerometer with sensitivity 9 mV/g was mounted on near to spindle frame. The 8 channel FFT analyser (DEWE 43 A) was used for

acceleration signal acquisition from accelerometer. Vibration measurements are thus usually taken near to the rotating component of a machine. Here when the machining is carried out on VMC, the vibration generated due to variation in parameters will directly affect cutting tool first and hence spindle. As the spindle revolving in vertical direction, orientation of accelerometer is kept vertical. The literature review [7,10] provides the suggestion for deciding orientation of accelerometer for tool condition monitoring. Based on the basis mentioned above and literature, the vertical orientation is incorporated. The time domain graph of acceleration (g) Vs time (sec) was recorded using DEWE software in real time. The sampling frequency of 20 kHz was used to convert analog acceleration into equivalent digital acceleration value. The vibration signals are acquired for face milling operation which was performed on Mild Steel C shaped hollow cuboid workpiece with dimensions 650mm*250mm*100mm using milling cutter of diameter 63 mm with 4 carbide inserts. The machining parameters recommended by KomGuide – Technical Manual was selected for all machining operations such as spindle speed 900 rpm, feed 2000 mm/min and depth of cut of 0.25 mm. The 6 machining operations were performed with 6 different insert conditions where speed, feed and depth of cut was kept constant as mentioned above and vibration signal was captured. The 6 different conditions are described as below in Table 1:

Table 1. Insert conditions for machining

Operation No.	Insert 1	Insert 2	Insert 3	Insert 4	Insert condition Category
1	New	New	New	New	A
2	New	New	New	Flank wear	B
3	New	New	New	Nose wear	C
4	New	New	New	Notch wear	D
5	New	New	Flank wear	Nose wear	E
6	New	New	Flank wear	Notch wear	F

3.1. Signal acquisition: The vibration signal was captured for all 6 operations and respective time domain plots acuqired in DEWE software as shown in figure 2. The sampling frequency of 20 kHz was selected according to Nyquist theorem [8]. Each operation is performed for time interval of 1 second. Initially rough machining was performed to eliminate oxide layer and unevenness of the workpiece and allowed to get stabilized. It is observed in figure 2 that the acceleration amplitude varies and rises as the fault condition changes.
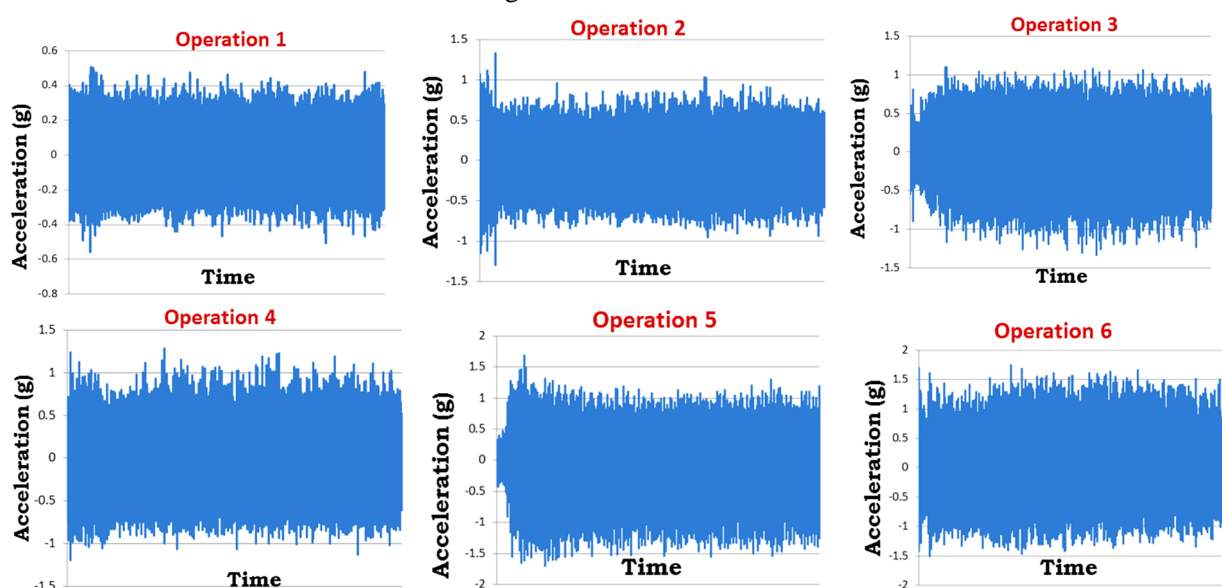

Figure 2. Signal acquisition in time domain for all machining operations

4. Result, discussion & validation using machine leaning approach

4.1. Feature extraction: The time domain features are nothing but the distinct characteristics observed directly from the acquired time domain plots. The VB code described by [14] was used in Microsoft Excel to extract statistical features from all 6 time domain plots of respective operations. Total 13 statistical features such as mean, standard error, median, mode, standard deviation, variance, kurtosis, skewness, range, minimum, maximum, summation, count were computed to serve as features. Here total 600 samples are considered (i.e.100 samples for each condition * 6 conditions = 600 samples).

4.2. Feature selection: The feature selection is the most significant step in machine learning approach as it selects most significant features amongst all. It reduces dimensionality; speed up the classification algorithm; increases classification accuracy and makes the results more comprehensible [15]. The all 13 features are fed to J48 algorithm and generated decision tree structure is shown in figure 3. It is observed that only 9 feature such as mean, standard error, median, standard deviation, kurtosis, skewness, range, minimum, maximum, found to be selected by J48 algorithm will serve to be most significant. Hence these 9 features are only used for feature classification.
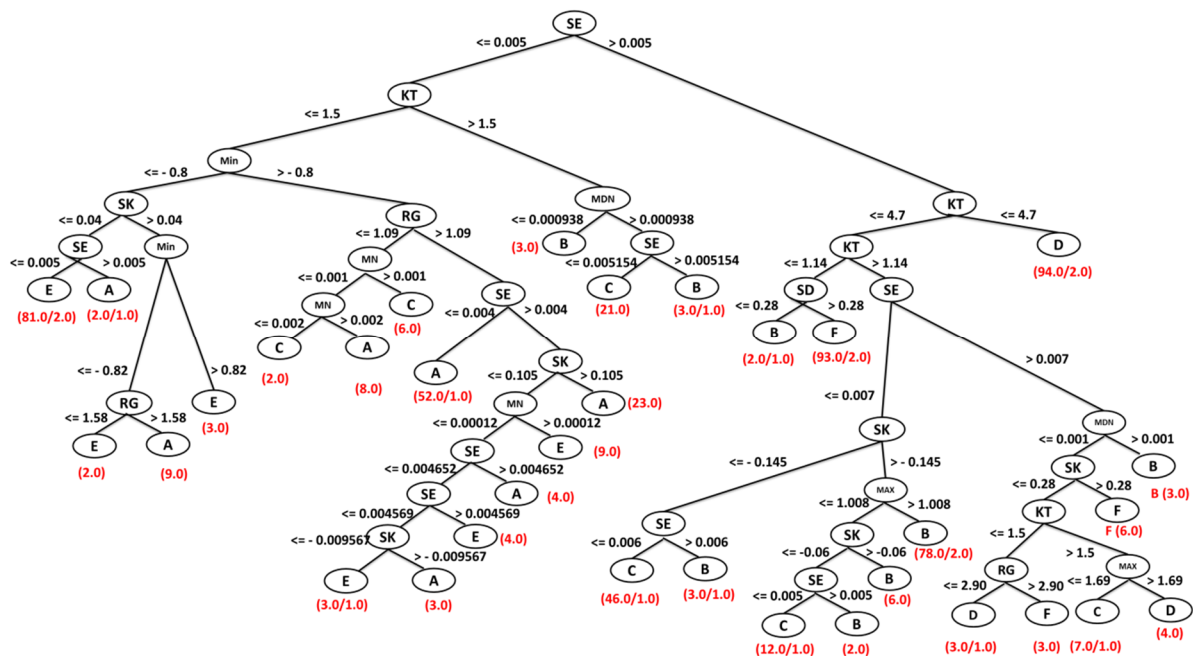

Figure 3. Result of decision tree J48 for feature selection

Nomenclature: MN: Mean, SE: Standard Error, MDN: Median, SD: Standard Deviation, KT: Kurtosis, SK: Skewness, RG: Range, MIN: Minimum, MAX: Maximum and A, B, C, D, E, F are the tool conditions as already

4.3. Feature classification: A data mining freeware named 'WEKA' was used for feature classification. The tree family classifiers give best classification accuracy amongst all other classifiers. That why comparison of tree family classifiers is advocated in this study to obtain best between them. We can use some other algorithms like K star algorithm, Naïve Bayes, LWL provided it should provide better classification accuracy. Here, the different conditions of milling cutter are classified using tree family classifiers i.e. J48, Logistic Model Tree and Random Forest algorithms based on 10-fold cross validation. Here classification validation is presented using confusion matrix as it describes categorization of distinctive tool conditions.

4.3.1 J48 classifier: In this experimentation, the classification accuracy for J48 algorithm is obtained as 85.5%. It is observed from confusion matrix shown in figure 4(a) that the diagonal element

represents the correctly classified samples, while non diagonal element represents misclassified samples. The confusion matrix for J48 tree shows that for 'A' condition (all inserts are new) of tool, 86 samples were correctly classified as 'All New'. For condition 'B' (three inserts new and one with flank wear), 81 samples were correctly classified as condition 'flank wear', whereas 12 samples were misclassified as 'C' (i.e. nose) condition and so on.

4.3.2 Random Forest Classifier: Random forest classifier creates assemblies of decision trees and then integrates them with each other to obtain improved, steady and truthful prediction. It is considered as combined approach as it facilitates classification and regression both. It put extra randomness to training model at time of developing the tree structure. It examines the most significant feature amongst a random subset than finding it at time of separating the node. Hence this gives better model because of broaden assortment. The classification accuracy for random forest is obtained as 88.16%. It is observed from confusion matrix shown in figure 4(b) that for 'A' condition (all inserts are new) of tool, 94 samples were correctly classified as 'All New'. For condition 'B' (three inserts new and one with flank wear), 84 samples were correctly classified as condition 'flank wear', whereas 10 samples were misclassified as 'C' (i.e. nose) condition and so on.

4.3.3 Logistic Model Tree Classifier: The principle of this classifier is based on collaborative approach, as it uses decision tree and logistic regression both classifiers. A piecewise linear regression model is obtained by this decision tree using linear regression models at its leaves. An LR model at every node in the tree is created using LogitBoost algorithm. After this the node is separated using the C4.5 criterion. A number of LogitBoost iterations that does not overfit the training data is identified from cross-validation. The classification accuracy for LMT is obtained as 88.33%. It is observed from confusion matrix shown in figure 4(c) that for 'A' condition (all inserts are new) of tool, 88 samples were correctly classified as 'All New'. For condition 'B' (three inserts new and one with flank wear), 84 samples were correctly classified as condition 'flank wear', whereas 10 samples were misclassified as 'C' (i.e. nose) condition and so on.
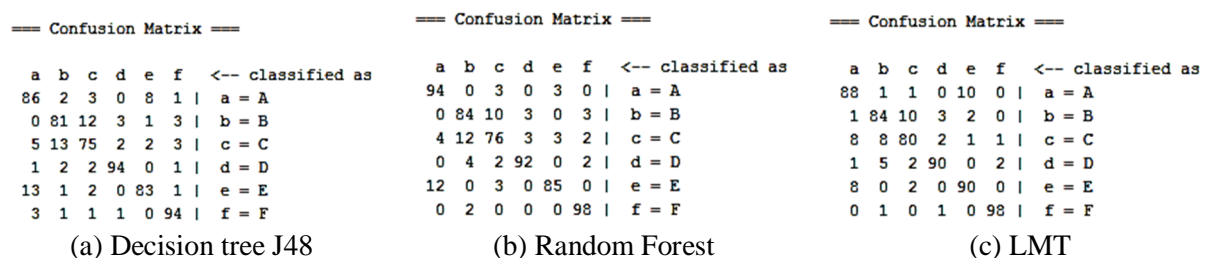
```
=== Confusion Matrix ===              === Confusion Matrix ===              === Confusion Matrix ===

 a  b  c  d  e  f  <-- classified as    a  b  c  d  e  f  <-- classified as    a  b  c  d  e  f  <-- classified as
86  2  3  0  8  1 |  a = A            94  0  3  0  3  0 |  a = A            88  1  1  0 10  0 |  a = A
 0 81 12  3  1  3 |  b = B             0 84 10  3  0  3 |  b = B             1 84 10  3  2  0 |  b = B
 5 13 75  2  2  3 |  c = C             4 12 76  3  3  2 |  c = C             8  8 80  2  1  1 |  c = C
 1  2  2 94  0  1 |  d = D             0  4  2 92  0  2 |  d = D             1  5  2 90  0  2 |  d = D
13  1  2  0 83  1 |  e = E            12  0  3  0 85  0 |  e = E             8  0  2  0 90  0 |  e = E
 3  1  1  1  0 94 |  f = F             0  2  0  0  0 98 |  f = F             0  1  0  1  0 98 |  f = F
```
  (a) Decision tree J48   (b) Random Forest   (c) LMT

Figure 4. Classification result for (a) J48 algorithm (b) Random Forest (c) LMT

4.3.4 Discussion on result: The table 2 represents comparison of various algorithms used for feature classification. It has been observed that logistic model and random forest algorithms yields very close accuracy. The table 2 shows that Logistic model tree algorithms performs best amongst all but when considered real time implantation of these algorithms for future prediction, the time taken to build model is a concern. In comparison of LMT and random forest, the time required to build the model is really less for random forest i.e. 0.6 seconds with the accuracy 88.16%. If accuracy is only constrain irrespective of time, then LMT served to be best. One can consider J48 algorithm too, if the time is constrain, as it required lesser time amongst all.

Table 2. Comparison of various algorithms used for feature classification

Sr. No.	Constrains used for classification (9 constrains selected by J48 tree)	Algorithm type → Parameter ↓	J48	LMT	Random Forest
1	Mean + Stand. Error + Median + SD + Kurtosis + Skewness + Range + Min + Max + Condition	Accuracy (%)	85.5	88.3333	88.1667
		Time for building model (seconds)	0.2	8.6	0.6

5. Conclusion

The machine learning based condition monitoring of milling cutter of vertical machining centre (VMC) was successfully demonstrated. The vibration signals acquisition for milling cutter was carried out with fault tool conditions. The Visual Basic (VB) code and script is used to extract statistical features and decision tree algorithm is used to select relevant features. The different conditions of tool are classified using tree family classifiers i.e. J48, LMT and random forest algorithms. Considering the classification accuracy and time required to build the model, the random forest observed to be best classifier. The LMT classifier yields slightly more accuracy than random forest but time required is considerable more than the random forest classifier. This approach is most suitable for real time implementation of tool fault diagnosis which ultimately reduces power consumption of drive system. This classification data can be used as history of particular instance and compared with same instant in present to predict future of the tool condition i.e. to build and incorporate a model using data fusion approach will be incorporated for future correspondence.

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