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Full Length Article

Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal

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ABSTRACT

This paper deals with the fault diagnosis of the face milling tool based on machine learning approach using histogram features and K-star algorithm technique. Vibration signals of the milling tool under healthy and different fault conditions are acquired during machining of steel alloy 42CrMo4. Histogram features are extracted from the acquired signals. The decision tree is used to select the salient features out of all the extracted features and these selected features are used as an input to the classifier. K-star algorithm is used as a classifier and the output of the model is utilised to study and classify the different conditions of the face milling tool. Based on the experimental results, K-star algorithm is provided a better classification accuracy in the range from 94% to 96% with histogram features and is acceptable for fault diagnosis.

1. Introduction

Cutting tool is an essential element in metal removal process. During continuous machining process, deterioration in cutting tool performance occurs due to the tool wear/breakage. Tool failure reduces the quality and varies the dimension of the product. The tool health is a key parameter in the manufacturing industries. Hence there is a need for an online tool condition monitoring (TCM) system, which provides a better health condition of the process and particularly the cutting tool by using continuous monitoring of certain parameters. This TCM system promises higher productivity with reduced maintenance cost and by saving idle time. Byrne et al. [6] made an in depth study on requirement of TCM system which is to be used for optimizing the tool usage, reducing the non-productive time, tool breakage detection, improving the process stability, etc.

Tool condition monitoring techniques include direct measurement and indirect measurement of tool wears. Direct measurement of cutting edge provides the most accurate information about physical deterioration of the cutting tool. LoCasto et al. [24] employed charge coupled device (CCD) Camera for tool wear measurement. Park et al. [31] applied direct measurement method using optical sensing techniques by computer vision systems. Ryabov et al. [35] used laser displacement sensor for online measurement of tool geometry in milling process. Prasad and Ramamoorthy [32] investigated and predicted the tool wears such as crater wear and flank wear using stereo vision method in turning process. These direct measurements provide the advantage of high accuracy in certain conditions only, but they have not yet proven to be very attractive either technically or economically. Currently, indirect measurements are more suitable for on-line in process applications. Indirect measurements are based on the relationship between the measuring data of the cutting process and the tool conditions. Machining process data such as cutting force signals [26,17,7], vibration signals [29], acoustic emission signals [43], current/power signals [2,37], etc. are acquired and relevant features are extracted from the data. Then the tool conditions are diagnosed using these extracted features and artificial intelligent techniques. However, a very few indirect methods are suitable for industrial applications, because the measured signals will be nonstationary and stochastic in nature.

There are two major steps involved in TCM system, first one to extract features from the ambiguous/noisy data and later one is to diagnose/classify the condition of the process/cutting tool using these extracted features. The features of the signal such as statistical features, histogram features, empirical mode decomposition (EMD) features, discrete wavelet transform (DWT) features, etc. and artificial intelligence techniques such as artificial neural network (ANN) [22,16], support vector machine (SVM) [27,41], Bayesian network [28,40], fuzzy neural network [23], hidden Markov

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model [13], decision tree [12], etc. can be seen in the current industries and manufacturing research field. So there is a need of studying the nature of the signal and their relationship with the tool condition, especially for an intermittent cutting process like face milling. Dutta et al. [9] investigated and compared the performance of fuzzy based neural network with the standard back propagation neural network for tool condition monitoring during face milling process using vibration and cutting force signals. They concluded that the proposed method is faster in computational steps and effectively applicable for on-line TCM system. Baek et al. [3] developed the digital signal processor board using autoregressive (AR) and band energy based methods for monitoring the breakage and chipping conditions of the face milling tool. They concluded that the developed processor is highly reliable in monitoring the cutting process and AR based model is more accurate in fault diagnosis than the band energy based model. Kuljanic and Sortino [21] proposed tool wear indicators; normalised cutting force (NCF) indicator and torque force distance (TFD) indicator in face milling by analysing the characteristics of cutting force signals during operation. They concluded that TFD indicator is better than the NCF, because in TFD indicator there is no need to determine the unworn tool cutting force and it is enough to determine the actual mean torque and mean cutting force. Ghosh et al. [14] correlated the different signals such as cutting force, vibration, spindle current and sound signals with the tool wear during face milling process using ANN technique. They validated the proposed method with the laboratory and the industrial employments. Hsueh and Yang [15] used the SVM technique in prediction of breakage in face milling cutter using cutting force signals. Mhalsekar et al. [25] investigated the vibration signals during face milling using recurrence quantification analysis (RQA) for monitoring the flank wear of tool insert. They concluded that RQA parameters such as entropy, percent laminarity, trapping time and percent recurrence are useful features for detecting the tool flank wear. Also control system plays a role in condition monitoring of the cutting tool. Rubio et al. [33] developed a system consisting of expert rule based modules for cutting parameter selection to the purpose of multi objectives such as tool life, material removal rate, surface roughness of the workpiece and stability in milling process. Rubio et al. [34] carried out the analysis of milling force control using fractional order holds method.

The time domain features such as statistical and histogram features are used in fault diagnosis of the machine component/cutting tool in the TCM system. Many researchers have carried out studies on TCM system using these time domain features. Sugumaran et al. [38] used the statistical features, decision tree and proximal SVM techniques for fault diagnosis of roller bearings. Alonso and Salgado [1] used the novel techniques in TCM system for detecting the tool wear in turning process using statistical features, ANN, singular spectrum analysis and cluster analysis. Elangovan et al. [10] studied the performances of Naïve Bayes and Bayes net classifiers through histogram and statistical features in turning operation using vibration signals. They concluded that statistical features yielded more classification accuracy than using histogram features. Sugumaran and Ramachandran [39] employed a fuzzy based classifier to diagnose the roller bearing conditions using histogram features and decision tree technique. Wang et al. [42] carried out the classification of different milling tool conditions using distributed Gaussian ARTMAP (adaptive resonance theory mapping) network by extracting the statistical parameters in time and frequency domains from the cutting force signals. Sakthivel et al. [36] achieved good classification results using the combination of principle component analysis (PCA) and decision tree in fault diagnosis of mono block centrifugal pump through the statistical features of vibration signals. Painuli et al. [30] investigated the different conditions of a single point cutting tool using statistical features of vibration signals. Gangadhar et al. [11] used the statistical features and decision tree technique for classifying the tool conditions in turning process using vibration signals. Jegadeeshwaran and Sugumaran [20] employed a clonal selection classification algorithm (CSCA) for condition monitoring of a hydraulic brake system using statistical features of vibration signals.

In the above literature, condition monitoring of machine element/cutting tool using different diagnostic techniques have been carried out. The features extraction methods such as statistical, DWT, EMD techniques with the different classifiers such as ANN, SVM, Naïve Bayes and decision tree exist in the current research area of condition monitoring, each having their own merits and demerits. A good diagnose tool will reduce errors of misjudgement of tool wear. It provides a quick and right decision about the condition of the cutting tool. The simplicity of histogram method and the K-star classifier have made them both compelling to use in fault diagnosis. K-star classifier has achieved appreciable results in some applications such as misfire detection of an IC engine [4] and classification of turning tool conditions [30]. In order to explore the possibility of using K-star algorithm in fault diagnosis of the milling tool and extensions to the range of its applicability, the combination of K-star model and histogram method is proposed. Studies on histogram features and K-star algorithm as a classifier are not reported in the literature of the milling process. The objective of this study is to evaluate the performance of the classifier with histogram features extracted from the vibration signals in the face milling process which can be applicable to develop an on-line TCM system for face milling. The objective can be summarised as to obtain an effective and efficient classifier with minimum response time in the design of TCM system of the face milling process. In this study, four different conditions (healthy, flank wear, breakage and chipping) of the face milling tool are considered. An attempt is made to use histogram features extracted from the vibration signals and the decision tree is used to select the salient features from the set of extracted features. K-star algorithm is used as a classifier in fault diagnosis of the face milling tool. The proposed method provided a better performance in classification of the face milling tool. Section 2 presents the experimental setup and procedure. Signal processing method called histogram approach is explained in Section 3, followed by feature reduction technique in Section 4. The classification tool adopted in this work is presented in Section 5. Results and discussion about the fault diagnosis of the face milling tool can be seen in Section 6, and Section 7 concludes the paper summarising the contribution of the proposed method.

2. Experimental setup

Experiments were carried out using universal milling machine [3M (AU) G all feed automatic] with selected machining parameters as shown in Table 1. A face milling cutter (6 Carbide inserts, Mitsubishi make: SEMT13T3AGSN-VP15TF) of 80 mm diameter and work-piece material of steel alloy 42CrMo4 were used in this study. Experimental setup consists of universal milling machine with data acquisition system as shown in Fig. 1.

Table 1
Experimental condition of face milling process.

Experimental condition	
Work material	42CrMo4/1.1225 steel alloy
Insert material	Carbide
Cutting speed	128 m/min
Feed rate	0.12 mm/insert
Depth of cut	0.5 mm
Fault conditions of the tool	Flank wear, breakage and chipping
Lubrication	Dry

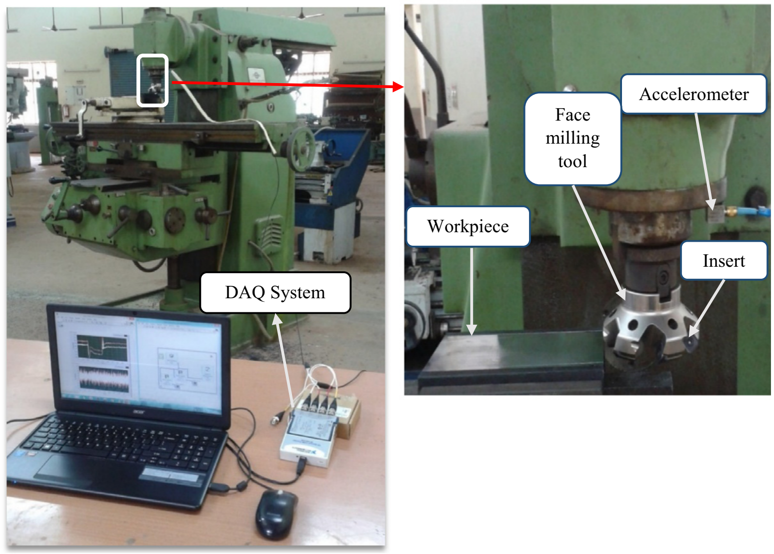


Fig. 1. Fault diagnosis of face milling tool test setup.

Experiments were conducted with four different conditions of the face milling tool, namely;

(a) Healthy.
(b) Flank wear.
(c) Cutting tip breakage (breakage).
(d) Chipping on rake face near cutting tip (chipping).

In the healthy condition of the tool, all six inserts are new/unworn inserts (Fig. 2(a)), whereas in fault condition among six inserts one is either flank wear (Fig. 2 (b)) or breakage (Fig. 2(c)) or chipping (Fig. 2(d)) and remaining five are healthy inserts and have been considered for analysis. Vibration signals are acquired using tri-axial IEPE accelerometer (MEAS 7132A) which is mounted on spindle housing. Data acquisition system (National Instruments DAQ 9234) is used to acquire the acceleration signals from the sensor with sampling frequency of 25.6 kHz and these signals are then processed by LabVIEW software.

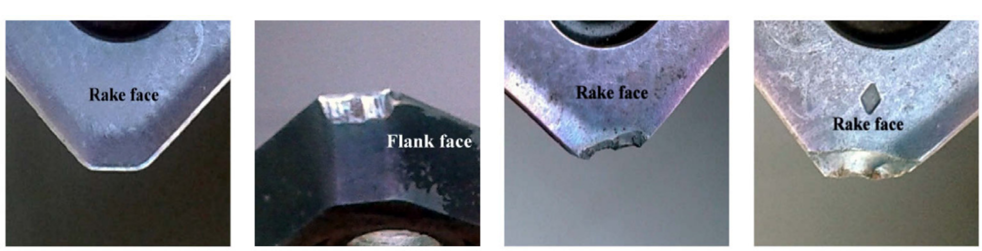
Initially, rough machining was carried out to remove the oxide layer and unevenness of the workpiece. The process was kept running for 2 or 3 min to stabilize the machine vibration before starting data acquisition. The initial few signals were not considered to avoid random vibration. The vibration signals were acquired for healthy and different fault conditions of the face milling tool. Total 200 samples were taken, out of which 50 samples from each condition of the tool for a time interval of 1 s at sampling frequency of 25.6 kHz. Fig. 3 shows the time-series plots in feed direction for different conditions of the face milling tool such as healthy, flank wear, breakage and chipping. The acceleration amplitude corresponding to fault condition shows slightly varied as compared to the healthy condition of the tool. It is quite difficult to diagnose the faults with the help of time-series plots. Generally, conventional data processing is computed in time or frequency domain and is not suitable for analysing non-stationary signals. Hence, there is a need of an artificial intelligent technique for analysing the signals and diagnosing the faults in milling tool based on the machine learning approach.

Machine learning is a scientific method to examine diagnostically the construction and the study of algorithms that can learn from the data. These algorithms build a model based on inputs and use that to make decisions or predictions, rather than following only explicitly programmed instructions. The flow chart of machine learning system for fault diagnosis of the face milling tool is as shown in Fig. 4.

3. Histogram features

Observing the time domain plots pertaining to all classes of the milling tool, one can notice that the acceleration amplitude is varied from class to class. The histogram plot is a better graph to show the range of variation in the plots. These variations are analysed by using bins of the signal which can be used as set features. Fig. 5 shows the histogram plots of the different conditions (healthy, flank wear, breakage and chipping) of the face milling tool.

The bin range is obtained from the vibration signals pertaining to all conditions of the milling tool being analysed. The amplitude



(a) Healthy (b) Flank wear (c) Breakage (d) Chipping

Fig. 2. Different conditions of face milling tool insert.

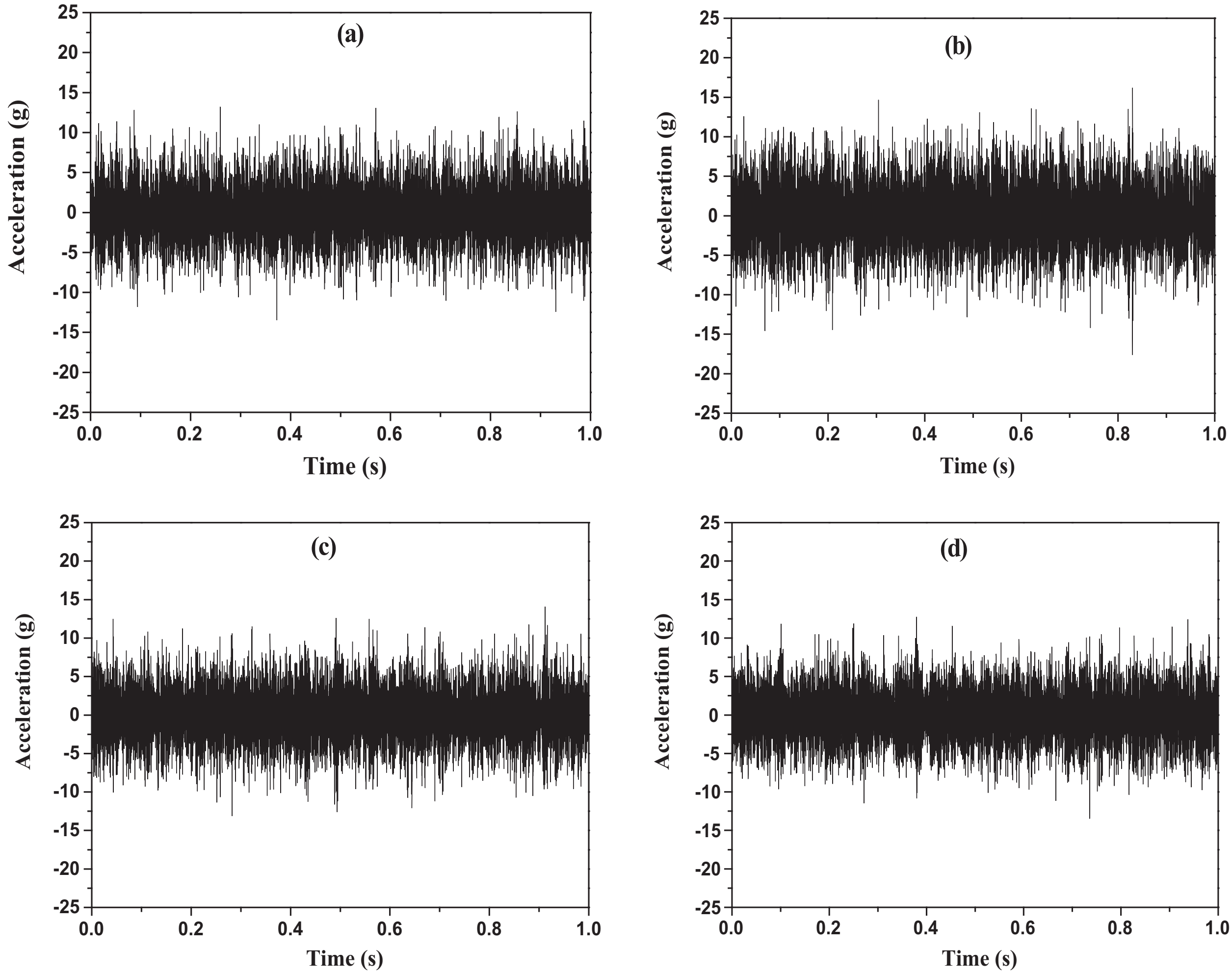


Fig. 3. Time-series plots with different tool conditions (a) healthy, (b) flank wear, (c) breakage and (d) chipping.

range (maximum value to minimum value of the vibration signals) is divided into number of sub ranges called bins which represent the x-axis of the histogram plot. The number of data points of the signals which lie on the corresponding bins are counted and represent the y-axis of the histogram plot. The objective here is to investigate the bins whose data points are same for a particular class but different from other classes. These values may be very small for a particular class of the milling tool but may be very large for another class of the milling tool.

The width of the bin should be fixed such that the height of bins is different for different class of the milling tool. It need not be true for all width of bins, but at least a few of them should follow this criterion so that it can be used as a feature for classifying the various conditions (classes).

4. Decision tree (J48 algorithm)

The decision tree technique is used to classify data into discrete forms using tree structured algorithms [5]. J48 technique has found immense applications such as medical, engineering, market research statistics, etc. The main purpose of the decision tree is to illustrate the structural information contained in the data. A standard tree is represented with J48 algorithm; it consists of a root node, a number of leaves, nodes and a number of branches. Each branch of a tree represents a chain of nodes from the root to a leaf and each node represents an attribute (or feature). The presence of a feature in a tree gives the information about the prominence of the associated feature. The procedure for making the decision tree and using the same for feature selection is explained below.

- The set of features is treated as an input to 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 the root of the tree to the node of the leaf.
- In each decision node in the tree, the most useful feature based on the estimation criteria can be chosen. The useful features identified based on the criteria which invoke the concepts of information gain and entropy reduction are explained below.

4.1. Information gain and entropy reduction

Information gain is defined as an expected reduction in entropy by partitioning the samples based on the feature. Entropy is defined as a measure of disorder present in the set of instances. By adding information, it reduces uncertainty. Information gain compares the entropies of the original system and the system after information added. The Information gain (S, A) of a feature 'A' to a set of examples 'S' can be expressed as,

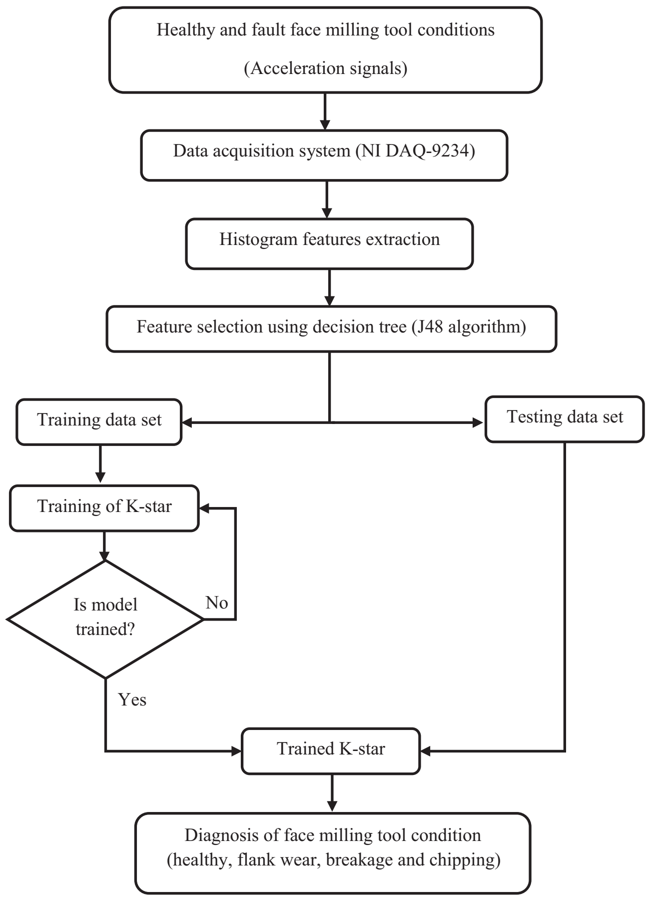


Fig. 4. Flow chart of fault diagnosis of the face milling tool.

$$\text{Gain } (S, A) = \text{Entropy } (S) - \sum_{v \in Value\ (A)} \frac{|S_v|}{|S|} \text{Entropy } (S_v) \tag{1}$$

where, '*Values* (*A*)' is the set of all possible values for attribute '*A*', 'S_v' is the subset of '*S*' of which feature '*A*' has a value '*v*' (i.e., $S_v = \{s \in S | A(s) = v\}$).

Note the first term in the Eq. (1) is the entropy of the original collection '*S*' and the second term is the expected value of the entropy after '*S*' is partitioned using feature '*A*'. The expected entropy described by the second term is the direct sum of the entropies of each subset 'S_v' weighted by the fraction of samples $|S_v|/|S|$ that belong to 'S_v'. Gain (*S*, *A*) is therefore the expected reduction in entropy caused by knowing the value of a feature '*A*'. Entropy is given by,

$$\text{Entropy } (S) = \sum_{i-1}^{c} -P_i log_2 P_i \tag{2}$$

where, '*c*' is the number of classes. 'P_i' is the proportion of '*S*' belonging to the class '*i*' [11]. In this study, histogram features were extracted from the vibration signals, total 200 samples (50 samples per each class) were collected from the experiment and used as input to the decision tree algorithm. The algorithm has given a set of salient features which has provided more information about the face milling tool conditions. The construction of the decision tree and the explanation about features selection can be seen in Section 6.2.

5. K-star classifier

The K-star algorithm uses entropic measure based on probability of transforming instance into another by randomly choosing between all possible transformations. Using entropy as appraise of distance has numerous utility. A consistency of approach in real, symbolic, missing value attributes makes it important. An instance based algorithm made for symbolic attributes fails in features of real value thus lacking in incorporated theoretical base. Approaches successful in feature of real values are thus in an ad-hoc fashion made to handle symbolic attributes. Handling of missing values by classifiers poses similar problems. Usually missing values are treated as a separate value, thought of as maximally different, substituted for average value, and otherwise simply ignored. In the present study a tool called WEKA (Waikato Environment for Knowledge Analysis) was used for classifying the tool condition. Entropy based classifier is a solution for these issues. The detailed explanation about K-star classifier can be referred by Cleary and Trigg [8].

For each class, a set of selected histogram features is used as input to the K-star model. The results of K-star classifier are mapped based on 10-fold cross validation. The detailed classification of the face milling tool based on selected features is explained in Section 6.3.

6. Results and discussion

This section deals with the fault diagnosis of the face milling tool using histogram features, decision tree and K-star classifier through the vibration signals. Total 200 samples, out of which 50 samples pertaining to all classes (condition of the tool) are considered for the analysis.

6.1. Histogram features

Following the criteria for extracting the histogram features as mentioned in Section 3, the bin width and bin range are selected based on the maximum and minimum values of the signals pertaining to all conditions and each bin is treated as a feature. Twenty different sets of histogram features were extracted from the vibration signals. Each set of features were treated as an input to the classifier and the results from the classifier were analysed. Fig. 6 shows the classification accuracies of K-star model for different sets of histogram features.

As seen from the Fig. 6, K-star model yielded a maximum classification accuracy of about 96.5% for both the thirty set and the forty set of histogram features. After this, the classification accuracy of the model has been attained in the range between 94% and 96% for different sets of features (for 50, 60, ..., 100 features). Table 2 depicts the set of thirty histogram features (f_1–f_{30}) and out of 200 samples, only two samples pertaining to each condition of the milling tool are shown in the table. In this table, the features $f_1, f_2, f_3, f_4, f_{27}, f_{28}, f_{29}$ and f_{30} are set to zero value for all conditions of the face milling tool.

Some of the extracted feature values are having significant differences for different conditions of the milling tool. Selecting those features is an important task for effective classification, doing it manually demands more expertise; however, the effectiveness of the features is not guaranteed. By using a suitable algorithm, best features are selected and also can yield better classification accuracy. The decision tree technique is a popular method for feature selection in the area of fault diagnosis.

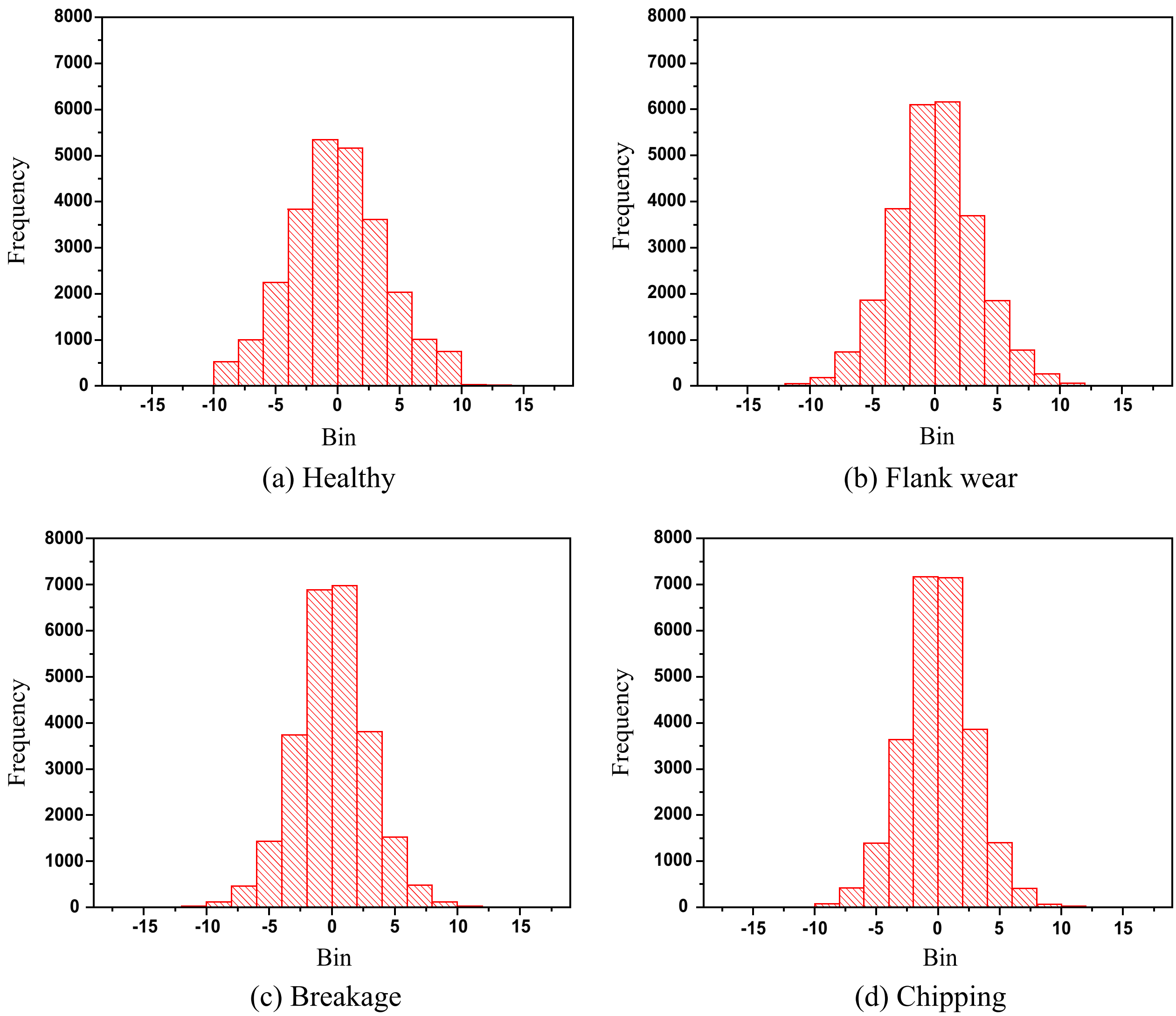


Fig. 5. Histogram plots for different conditions of the face milling tool.

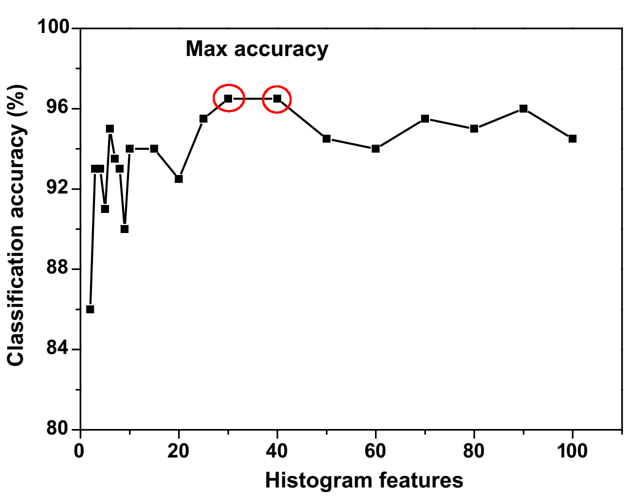


Fig. 6. K-star classification accuracy for different sets of histogram features.

6.2. Feature selection using decision tree

All extracted features were treated as an input to the decision tree for selecting the best features which helps to improve the classification accuracy of the diagnostic tool. The output of the decision tree is formed as a tree like structure as shown in Fig. 7. The decision tree has been constructed for the set of thirty histogram features in such a way that, when the feature f_{21} is greater than 69 and f_{23} is greater than 13, it is classified as 'healthy' face milling condition. When the feature f_{21} is greater than 69 and f_{23} is less than or equal to 13, then it is classified as 'flank wear' condition, and the remaining classes (breakage and chipping) have been organised in the tree when the feature f_{21} attains less than or equal to 69. The features $f_6, f_8, f_9, f_{17}, f_{21}, f_{22}$ and f_{23} are selected as significant features from the tree and these features are used as an input to the classifier.

6.3. Classification using K-star

In this study, K-star algorithm was used as a classifier to distinguish the face milling tool condition. 50 samples were considered

Table 2
Histogram features.

Face milling tool condition	Sample No.	Histogram features																					
		f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}	f_{17}	f_{18}	f_{19}	f_{20}	f_{21}	f_{22}	f_{23}	f_{24}	f_{25}	f_{26}
Healthy	1	2	4	15	42	120	323	833	1734	2915	4126	4820	4159	2881	1775	990	490	236	92	25	14	4	0
	2	1	5	25	47	148	393	889	1593	2792	4081	4956	4174	2829	1731	977	508	263	120	42	16	7	3
Flank wear	1	2	2	11	33	78	237	693	1423	2863	4383	5146	4566	3047	1753	819	335	143	51	13	2	0	0
	2	0	1	8	22	67	246	629	1482	2780	4436	5215	4688	3009	1686	824	337	124	33	12	1	0	0
Breakage	1	0	0	1	10	37	114	357	1011	2414	4755	6727	5404	2842	1260	474	142	44	6	2	0	0	0
	2	0	1	4	10	32	145	394	988	2446	4898	6469	5379	2795	1259	531	178	55	15	1	0	0	0
Chipping	1	0	0	1	4	19	77	349	1047	2389	4849	6613	5422	2984	1236	445	139	18	7	1	0	0	0
	2	0	0	0	2	19	94	317	1032	2450	4856	6609	5416	2929	1260	470	123	19	4	0	0	0	0

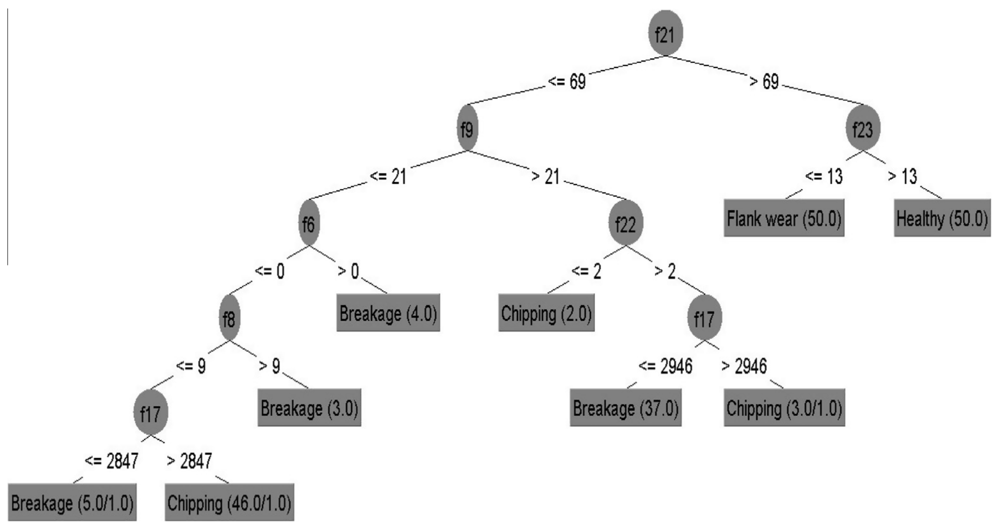


Fig. 7. Decision tree for a set of thirty histogram features.

for each condition of the tool (for 4 classes 200 samples). This data were divided into two; training data set and testing data set. 65% (33 samples per each class) of the samples were used as training set and remaining 35% (17 samples per each class) of the samples were used for testing the model. K-star model has provided 100% classification efficiency for training dataset, whereas 92.7% for testing dataset. Indira et al. [19,18] suggested a minimum number of samples (less than ten per each class) required to distinguish the fault conditions in the area of machine learning approach. However, 50 samples per each class were used for classifying the face milling tool conditions in order to get a statistically stable classification accuracy. The K-star model has mapped the classification of the milling tool based on 10-fold cross validation test mode. The output of the classifier is the confusion matrix which illustrates the classification of different conditions of the face milling tool. The confusion matrix for the given set of histogram features (30 features) of vibration signals is as shown in Table 3.

As seen from the confusion matrix, the diagonal elements represent the correctly classified instances (samples), whereas non diagonal elements represent the misclassified instances. For 'healthy' condition of the milling tool, all 50 instances were correctly classified as 'healthy'. While in case of 'breakage' condition, 43 out of 50 instances were correctly classified as 'breakage', whereas 7 instances of 'breakage' were misclassified as 'chipping' condition and so on. The detailed accuracy in classification is explained with the Table 4 below.

Table 4 shows the detailed accuracy of the K-star model by class, where the true positive rate (TP rate) and false positive rate (FP rate) indicate the significance in judging the quality of the model; for good classification TP rate implies '1', while the FP rate implies '0'. For the given vibration signals, TP rate of healthy condition is 1 which indicates all 50 instances were correctly classified as healthy. In case of breakage condition, TP rate is about 0.86 which indicates 43 out of 50 instances were correctly classified as breakage, whereas 7 instances of breakage were misclassified as chipping which is represented by a FP rate of 0.047 at chipping condition and so on. Here, out of 200 instances, 7 instances were misclassified by a K-star algorithm with the overall classification accuracy 96.5% for the set of thirty histogram features. Ultimately, one can notice that 100% (50 instances) of healthy instances were

Table 3
K-star confusion matrix.

a	b	c	d	Class
50	0	0	0	a-Healthy
0	50	0	0	b-Flank wear
0	0	43	7	c-Breakage
0	0	0	50	d-Chipping

Table 4
Detailed accuracy classification of K-star.

TP rate	FP rate	Precision	Recall	*F*-measure	ROC area	Class
1	0	1	1	1	1	Healthy
1	0	1	1	1	1	Flank wear
0.86	0	1	0.86	0.925	0.992	Breakage
1	0.047	0.877	1	0.935	0.993	Chipping

correctly classified, whereas none of the instances of fault conditions were represented as healthy condition. This can be accepted as a reasonably good performance of the classifier. Also from the observation in Fig. 6, classification accuracies for different sets of features (50, 60, ..., 100 features) by K-star attain the range between 94% and 96%, which can be considered in the area of fault diagnosis. Hence, the K-star technique can be suggested for fault diagnosis of the face milling tool.

7. Conclusion

This article has presented the vibration based fault diagnosis of the face milling tool using machine learning techniques. The histogram features were extracted from the vibration signals under healthy and different fault conditions (flank wear, breakage and chipping) of the milling tool. Significant features were selected by the decision tree technique and classification of the tool has been carried out using K-star algorithm. Experimental investigation has proved that the K-star model is able to achieve the classification accuracy in the range from 94% to 96% for the given experimental condition and workpiece of steel alloy 42CrMo4in the applications of the face milling process. In case of signal processing using histogram technique, it has served the purpose to capture different vibration patterns. Also the K-star classifier is able to assess the tool condition with a minimum response time (about less than 0.01 s), which is very much essential for automated manufacturing system. Hence the K-star algorithm is an effective technique and can be recommended in the applications of TCM system of the face milling process with the histogram features extracted from the acquired vibration signals.

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