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Use of Discrete Wavelet Features and Support Vector Machine for Fault Diagnosis of Face Milling Tool

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Abstract: This paper presents the fault diagnosis of face milling tool based on machine learning approach. While machining, spindle vibration signals in feed direction under healthy and faulty conditions of the milling tool are acquired. A set of discrete wavelet features is extracted from the vibration signals using discrete wavelet transform (DWT) technique. The decision tree technique is used to select significant features out of all extracted wavelet features. C-support vector classification (C-SVC) and ν-support vector classification (ν-SVC) models with different kernel functions of support vector machine (SVM) are used to study and classify the tool condition based on selected features. From the results obtained, C-SVC is the best model than ν-SVC and it can be able to give 94.5% classification accuracy for face milling of special steel alloy 42CrMo4.

Keywords: Fault diagnosis, face milling, decision tree, discrete wavelet transform, support vector machine.

1 Introduction

In modern manufacturing industries, there is an increasing need for reducing cost, high quality products with the healthy condition of the machine/machine tool. Damage/fault condition of the tool reduces the quality of the products or increases the quantity of rejected products. In order to maintain the condition based manufacturing, fault diagnosis and prognosis are essential. Tool wear and breakage modes are predominantly occur in machining process. These modes can be predicted by direct and indirect approaches. Direct measurement of tool condition using vision based and/or optical sensor can capture the actual changes in the geometry of the tool, but continuous contact of the tool-workpiece and the presence of coolant during process limit the direct measurement approach. In indirect approach, tool condition is correlated to the suitable sensor signals. Tool condition monitoring (TCM) system works based on signals such as vibration, current, cutting force, acoustic emission, etc. which are acquired from the sensors during the machining process. The TCM system provides an useful information about current condition of the tool during the process, consequently it improves the economy of production.

Signal processing methods are used to analyse the data and some salient features are then extracted from the acquired raw signals. These extracted and selected features are used to predict the tool condition using artificial intelligence techniques. Numerous signal

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processing methods are available in the field of condition monitoring system. DWT analysis is much more efficient, less computation and it is 98% reliable to identify small changes in acoustic emission (AE) and current signals of the drilling process for detection of tool breakage [Li, Dong and Yuan (1999)]. Further Wu et al. [Wu, Escande and Du (2001)] implemented a real time tool condition monitoring in transfer drilling station based on DWT using current signal. Li et al. [Li and Guan (2004)] proposed an algorithm consists of wavelet denoising, discrete wavelet analysis and FFT for detection of cutting edge fracture of end milling tool using feed motor current signals. They found that this algorithm is not applicable for light cutting operations, because it is difficult to extract the information from the current signal of low cuts for fault detection. Choi [Choi, Narayanaswami and Chandra (2004)] used the DWT and linear regression methods for estimating the tool wear in ramp cuts in end milling process. Franco-Gasca et al. [Franco-Gasca, Herrera-Ruiz, Peniche-Vera et al. (2006)] applied the sensorless method for tool condition monitoring in a drilling process using DWT and driver current signals. Gong et al. [Gong, Obikawa and Shirakashi (1997)] compared the wavelet transform with the Fourier transform using cutting force signal for monitoring of tool flank wear during turning process and they found that the wavelet analysis is more reliable, sensitive and faster than Fourier analysis. Berger et al. [Berger, Minis, Harley et al. (1998)] studied the chatter and non-chatter cutting process through wavelet analysis using cutting force signals in turning operation. Klocke et al. [Klocke, Reuber and Kratz (2000)] computed wavelet parameters for finding variations in cutting force signals of ball end milling under different tool condition and they found that, this technique is reliable for monitoring the ball end milling tool. Suh et al. [Suh, Khurjekar and Yang (2002)] investigated the milling process based on the DWT analysis to find stability in machining process using cutting force signals. Yesilyurt [Yesilyurt (2006)] found the variations in mean frequency of the scalogram of vibration signals with different feed rates in breakage detection of end milling tool. Kim et al. [Kim, Lee, Lee et al. (2007)] demonstrated that DWT is the most effective technique among various signal processing techniques such as fast Fourier transform, Wigner-Ville distribution, short time-frequency transform and DWT in damage detection of rotor system using vibration signals. Kumar et al. [Kumar and Singh (2013)] used the Symlet wavelet and vibration signals for measuring the defect width on the outer race of the roller bearing.

The classification tools have played a vital role in the TCM system for classifying the different tool condition. A good diagnose tool reduces error of misclassification for TCM system. Hong et al. [Hong, Rahman and Zhou (1996)] used a neural network technique for condition monitoring of turning tool based on wavelet decomposition. They found that the wavelet features of cutting force signal had a low sensitivity to the changes in machining conditions. Wang et al. [Wang, Mehrabi and Kannatey-Asibu (2002)] found 97% accuracy in tool state detection for TCM of turning process based on hidden Markov models and DWT features using vibration signals. Cho et al. [Cho, Asfour, Onar et al. (2005); Hsueh and Yang (2009)] used the support vector machine (SVM) technique for tool breakage detection in a milling process using cutting force dynamometer and spindle displacement sensor. Widodo et al. [Widodo and Yang (2007)] provided a review of various applications of the SVM technique on fault diagnosis and machine condition monitoring system. Vernekar et al. [Vernekar, Kumar and Gangadharan (2014)] diagnosed the faults in deep groove ball bearing using SVM and wavelet features. Saimurugan et al. [Saimurugan, Ramachandran, Sugumaran et al. (2011)] used statistical features and SVM for fault diagnosis of rotational mechanical system using vibration signals.

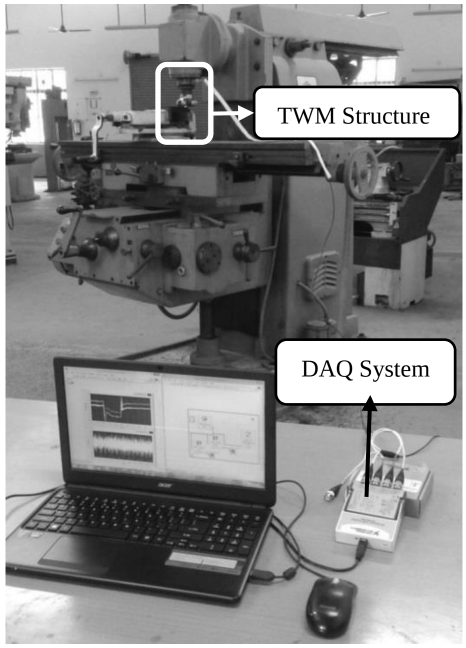
The aforementioned literature motivates to do work on the TCM system with an efficient and effective intelligent technique as well as signal features. The combination of DWT and SVM techniques is not reported in the literature of tool condition monitoring of the milling process. This study aims to diagnose the faults in face milling tool based on machine learning approach. Vibration signals under healthy and fault conditions of the tool have been used to extract the DWT features by using MATLAB code. Significant wavelet features such as V1, V2, V3, V5 and V6 have been selected from extracted features using decision tree. C-SVC and *ν*-SVC models of SVM have been used to classify the different condition of the tool based on these selected features and their classification accuracies were compared.

2 Experimental setup

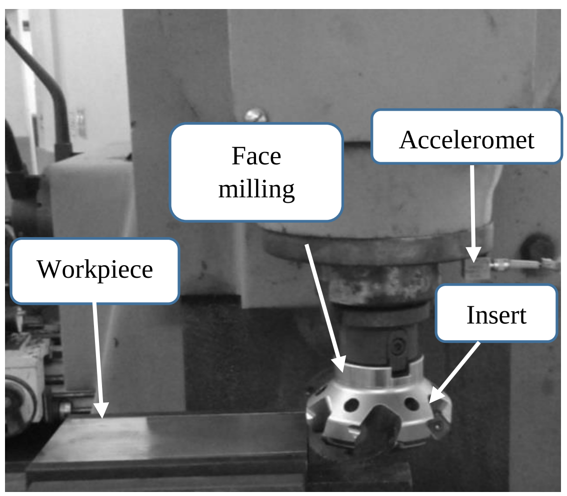
Experiments were carried out using universal milling machine with machining parameters as listed in Tab. 1. Experimental setup consists of universal milling machine with data acquisition (DAQ) system as shown in Fig. 1. Face milling tool with 6 carbide inserts (Mitsubishi make: SEMT13T3AGSN) of 80 mm diameter and work-piece material of special steel alloy (42CrMo4) were used in this work.

Table 1: Experimental condition of face milling process

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



(a) Experimental setup

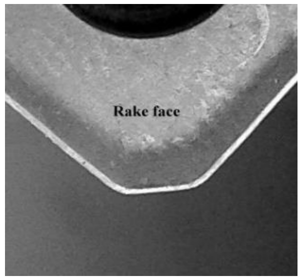


(b) Tool-Workpiece Material (TWM) structure with accelerometer

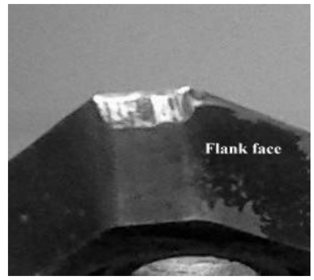
Figure 1: Fault diagnosis of face milling tool test setup

Experiments were conducted with four different conditions of the tool as shown in Fig. 2, out of which one is healthy and three are fault conditions, namely;

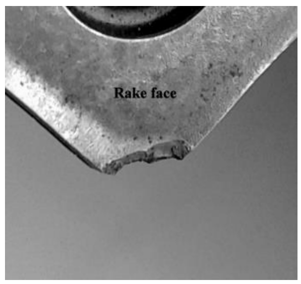
a) Flank wear
b) Cutting tip breakage (breakage)
c) Chipping on rake face near cutting tip (chipping)



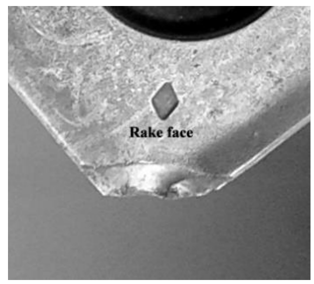
a) Healthy



b) Flank wear



c) Breakage



d) Chipping

Figure 2: Different conditions of face milling insert

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

Initially, rough machining was carried out to remove the oxidized layer and unevenness of the workpiece. The process was kept running for two or three minutes to stabilize the machine vibration before starting data acquisition. The first few signals were not considered to avoid random vibration. The vibration signals were acquired for healthy and different faulty conditions of the milling tool. Total 200 samples were taken, out of which 50 samples for each condition of the tool for a time interval of 1 second at sampling frequency of 25.6 kHz. Fig. 3 shows the time-series plots in feed direction for different conditions of the milling tool such as healthy, flank wear, breakage and chipping. The acceleration amplitude corresponding to faulty conditions shows slightly higher as compared to the healthy condition of the tool. It is quite difficult to diagnose the faults with the help of time-series plots. Hence, there is a need of an artificial intelligent technique for analysing the signals and fault diagnosis of milling tool based on the machine learning approach, which can be seen in forthcoming sections.

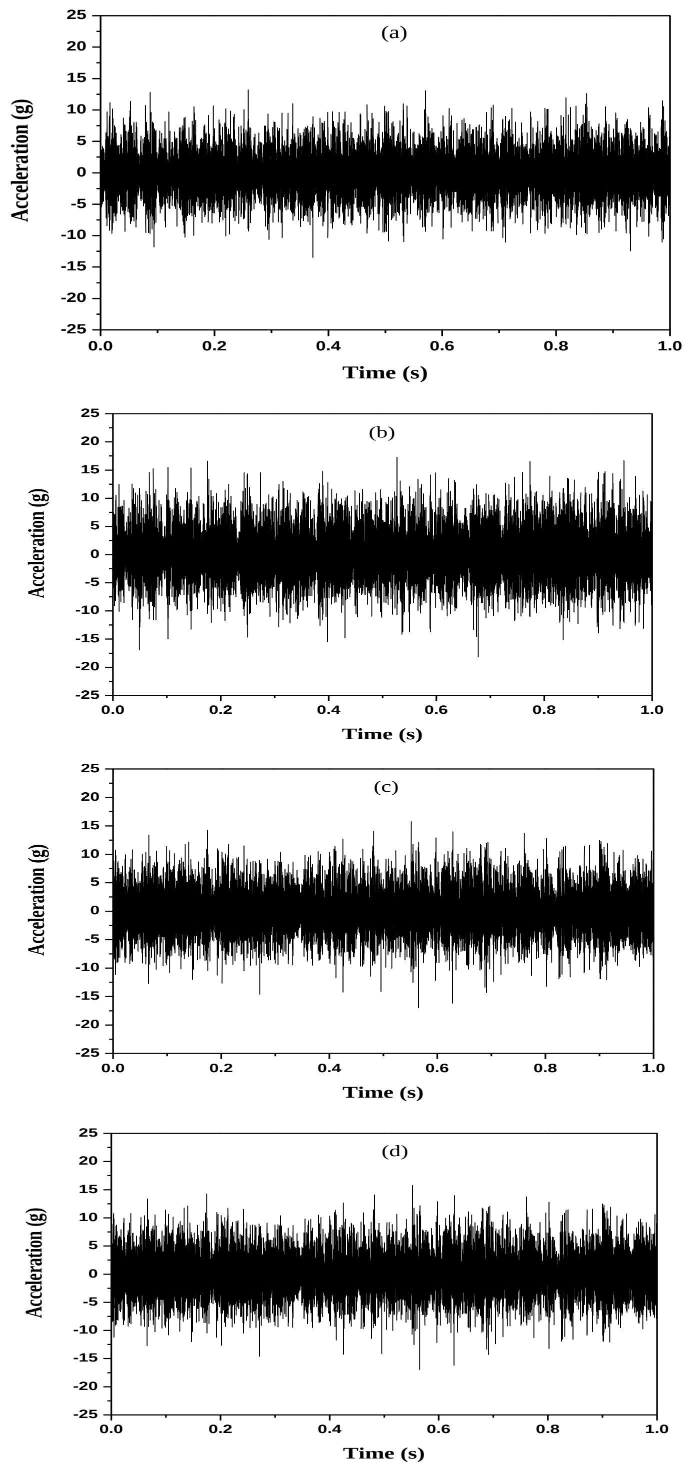


Figure 3: Time-series plots of (a) healthy, (b) flank wear, (c) breakage and (d) chipping

3 Machine learning approach

Machine learning is a scientific method to examine diagnostically the construction and study of algorithms that can learn from data. These algorithms build a model based on inputs and using that to make decisions or predictions, rather than following only explicitly programmed instructions. The acquired signals are used to analyse the condition of the machine/machine tool by extracting some characteristics associated to the signal such as statistical features, histogram features, DWT features, empirical mode decomposition (EMD) features, etc. which are correlated to the tool condition. These extracted features are fed to the classifier for predicting the tool states. The flow chart of the TCM system for face milling process with DWT and SVM methods is as shown in Fig. 4.

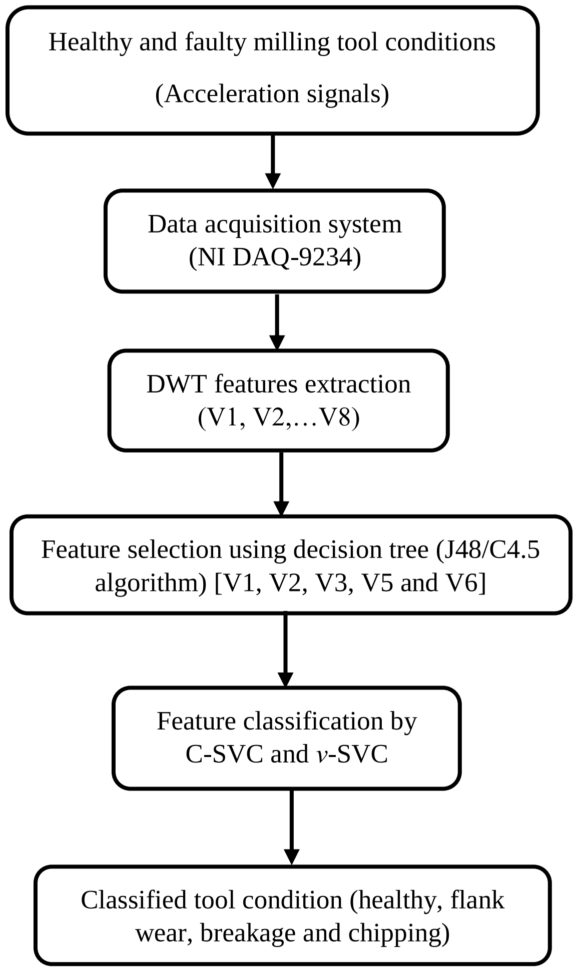


Figure 4: Flow chart of TCM system using DWT and SVM

3.1 Discrete wavelet transform (DWT) features

The acquired signal can be represented in another form of a signal using basic function, this is called transformation of a signal. It does not change the information which exists in the signal. The wavelet transform is a mathematical tool that transforms a signal into a different form (in the time-scale domain, a series of wavelet coefficients, etc.) using a wavelet function. A wavelet function is a short wave with finite energy characteristics [Yan, Gao and Chen (2014)]. Wavelet transform represents the signal in time-frequency domain. Applications of wavelet transform can be seen in various fields such as mathematics, science and engineering as watermarking, image registration, signal denoising, compression, feature extraction, time-frequency analysis, etc. [Zhu, Wong and Hong (2009)]. DWT is one of the wavelet transforms and it was evolved by Mallat [Mallat (1989)] with fast algorithm based on the conjugate quadratic filters. The DWT in the mathematical form of a signal *x(t)* is expressed as [Yan, Gao, Chen et al. (2014)];

$$dwt\ (j.k) = \frac{1}{\sqrt{2^j}} \int x(t)\psi^* \left(\frac{t-k2^j}{2^j}\right) dt \tag{1}$$

The DWT uses low-pass wavelet filter $h(k)$ and high-pass wavelet filter $g(k)=(-1)^k h(1-k)$. These wavelet filters work based on selected wavelet function $\psi(t)$ and its corresponding scaling function $\phi(t)$, expressed as,

$$\left.\begin{aligned} \phi(t) &= \sqrt{2}\sum_k h(k)\phi(2t-k) \\ \psi(t) &= \sqrt{2}\sum_k \mathrm{g}(k)\phi(2t-k) \end{aligned}\right\} \tag{2}$$

With $\sum_k h(k) = \sqrt{2}$ and $\sum_k g(k) = 0$.

Using these filters, the signal is decomposed into two components. One is low frequency component and another one is high frequency component as,

$$\left.\begin{aligned} a_{j,k} &= \sum_m h(2k-m)a_{j-1,m} \\ d_{j,k} &= \sum_m \mathrm{g}(2k-m)a_{j-1,m} \end{aligned}\right\} \tag{3}$$

Where $a_{j,k}$ is 'approximation' coefficient and $d_{j,k}$ is 'detail' coefficient. Approximation and detail coefficients represent low frequency components and high frequency components of the signal respectively. Approximation and detail coefficients are produced at multiple scales by iterating the process on the approximation coefficients of each scale. The entire process is represented as tree-structure as shown in Fig. 5.

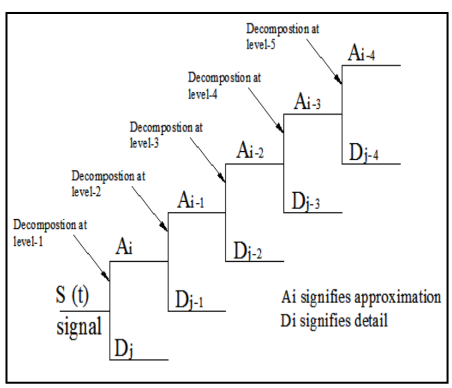


Figure 5: Wavelet decomposition tree

These coefficients represent a set of features. Based on the scale and position of wavelet, the wavelet coefficients represent the characteristics of a signal. The set of such features obtained using DWT termed as feature vector and it is given by Vernekar et al. [Vernekar, Kumar and Gangadharan (2014)],

$$v_i^{dwt} = \{v_1^{dwt}, v_2^{dwt}, \ldots v_{12}^{dwt}\}^T \quad (4)$$

Where v_i^{dwt} component is related to the individual resolutions and can be computed as follows,

$$v_i^{dwt} = \frac{1}{ni}\sum_{\mathrm{j=1}}^{\mathrm{ni}} \mathrm{W}_{\mathrm{i,j}}^2 \;\; ; \;\; \mathrm{i} = 1,2, \ldots .12 \quad (5)$$

Where $n_1=2^{12}$, $n_2=2^{11}$,….. $n_{12}=2^0$,

v_i^{dwt} is the i^{th} feature element in a DWT feature vector, n_{i} is the number of samples in an individual sub-band. $W_{i,j}^2$ is the j^{th} coefficient of the i^{th} sub-band. v_i gives the mean square value of the decomposed signal at different levels.

3.2 Feature selection

The process of feature selection is a different task as compared to feature extraction; in this case, no new features are generated. It is a process of choosing a subset of 'M' features from the existing set of 'N' features (M<N), so that feature space is optimally decreased based on certain criterion [Blum and Langley (1997)]. In machine learning system the role of the feature selection are as follows;

- to decrease the feature space dimensionality,
- to accelerate a learning algorithm,
- to enhance the predictive accuracy of a classification algorithm and
- to enhance the understandability of the learning results.

3.2.1 Decision tree (J48 algorithm)

Decision trees are methodologies used to classify data into discrete forms using tree structured algorithms. This technique has found immense applications in medical, engineering field, market research statistics, marketing and customer relations. The main purpose of the decision tree is to expose the structural information contained in the data. A standard tree represented with J48 algorithm, it consists of a root node, a number of leaves, number of nodes and 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 exploiting the same for feature selection is characterized as follows [Gangadhar, Kumar, Narendranath et al. (2014)].

- 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 the root of the tree to the 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 based on the criteria which invokes the concepts of information gain and entropy reduction are explained below.

3.2.2 Information gain and entropy reduction

Information Gain is defined as an expected reduction in entropy by making partition 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 is added. The Information Gain (S, A) of a feature 'A' to a set of examples 'S' can be expressed as,

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

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

Note, the first term in the equation for Gain 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,

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

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

3.3 Support vector machine classifier

Support vector machine (SVM) is one of the supervised learning methods used for classification. SVM is based on concept of decision planes, that defines decision boundaries and it works based on statistical learning method. It classifies the data points such that creating a hyper plane or classification plane between the classes. Fig. 6 shows the classification of two different classes which represent triangles for positive class and circles for negative class. SVM tries to classify these data points (positive and negative classes) by creating an optimal separable hyper-plane. The distance between the two dotted lines (bounding planes) is called margin. The main objective of SVM is to maximize the margin and minimize the generalization error. The data points which are nearer to the bounding planes are called support vectors. These support vectors help to define the margin and contain all the information about classification [Widodo and Yang (2007)].

Consider a training data set $\{(x_i, y_i)\}$; $i=1$ to L, $x_i \in R^n$, $y_i \in (1, -1)$ where L indicates total number of data points. x_i is the input vector and y_i is indicator vector. It is required to determine the hyper plane, which separates the data points linearly into two classes (triangles and circles). $y_i \in (1, -1)$ is concerned with the two types of classes namely triangles and circles. For the hyper plane $f(x)=0$ which separates the given data is obtained as a solution to the following optimization problem.

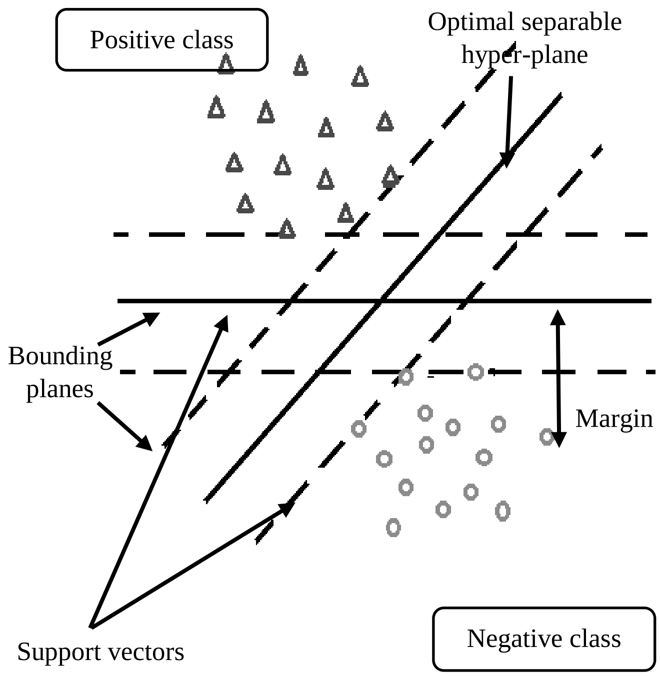


Figure 6: Classification of two classes using SVM

$$Minimize \quad \frac{1}{2}\,||w||^2 + C\sum_{i=1}^{L}\xi_i \tag{8}$$

$$Subject\ to \quad \begin{cases} y_i\,(w^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0\,; \qquad i = 1\ to\ L \end{cases} \tag{9}$$

Where, 'ξ' is a slack variable which measures the distance between the margin and the examples x_i, 'b' is the bias, C>0 is the constant representing penalty parameter and 'w' is weight vector.

After training, for any new set of features prediction of its class is possible using the decision function. The decision function is a function of 'w' and 'γ', which is given below.

$$f(x) = sign\,(w^T x - \gamma) \tag{10}$$

If the value of *f(x)* is positive, then a new set of features belongs to class triangles; otherwise it belongs to class circles [Saimurugan, Ramachandran, Sugumaran et al. (2011)]. C-SVC and *ν*-SVC models [Vernekar, Kumar and Gangadharan (2015)] of SVM are used for fault diagnosis of the face milling tool.

4 Results and discussion

In this study, 50 vibration signal samples were acquired for each condition of the milling tool. Discrete wavelet features were extracted from the signal using DWT technique and all features were fed to the decision tree technique. C-SVC and *ν*-SVC models of SVM with four kernels have been used for classification of milling tool conditions.

4.1 Features extraction

From vibration signals, eight discrete wavelet features (V1, V2… V8) were extracted for each class of the tool. Tab. 2 shows the discrete wavelet features using the DWT, out of 50 samples only two samples relating to each condition of the tool are tabulated. These features were treated as an input to the decision tree for the selection of the salient features which provide best classification accuracy.

Table 2: Discrete wavelet features of vibration signals

Face milling tool condition	Sample No.	Wavelet coefficient							
		V1	V2	V3	V4	V5	V6	V7	V8
Healthy	1	6.1	27.	30.	17.1	13.	5.5	2.14	1.2
	2	6.3	29.	31.	19.0	13.	5.9	2.67	1.3
Flank wear	1	4.5	21.	26.	20.4	13.	5.6	2.44	1.3
	2	4.4	20.	25.	20.2	12.	6.0	1.81	1.3
Breakage	1	2.6	12.	18.	21.7	15.	5.5	2.49	1.3
	2	2.6	12.	19.	22.4	13.	5.6	2.80	1.4
Chipping	1	2.2	10.	16.	20.5	12.	5.4	2.17	1.3
	2	2.2	10.	17.	19.4	11.	5.3	2.71	1.2

4.2 Feature selection

For feature selection the J48 algorithm was used, all extracted wavelet features pertaining to four classes were fed to the algorithm and formed decision tree is depicted in Fig. 7. The rectangular blocks indicate classes (condition of the tool). Within the parenthesis, there are two numbers separated by a slash in rectangular blocks. The first number (in case of two numbers) or only the number represents the number of data points (samples) which helps in making the decision.

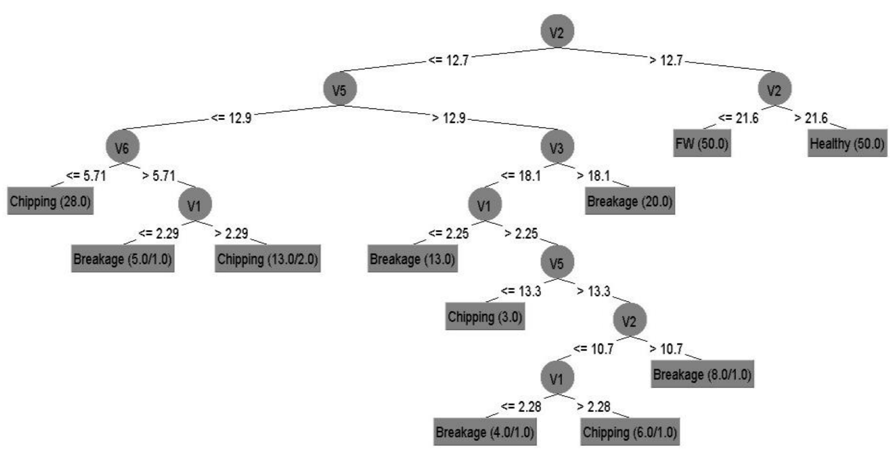


Figure 7: Decision tree

As seen from the Fig. 7, V2 feature is a root node of the tree, based on this feature (V2) the tree structure was carried out. When V2 value is greater than 21.6, it is classified as a healthy condition, while the V2 value is greater than 12.7 and less than or equal to 21.6, it classified as a flank wear and so on. The five features such as V1, V2, V3, V5 and V6 were selected out of eight wavelet features from the decision tree. The detailed accuracy classification is discussed in the following section.

4.3 Classification using SVM

The selected wavelet features were treated as an input and fed to the SVM models. Results obtained from the models were compared using different kernel functions such as linear, radial basis function (RBF), polynomial and sigmoid of SVM as shown in Tab. 3.

Table 3: Classification accuracy of SVM with different kernels

SVM kernel	SVM Model	Classification accuracy	Support vectors
Linear	C-SVC	93.5%	92
	ν-SVC	93%	165
RBF	C-SVC	92.5%	176
	ν-SVC	93%	165
Polynomial	C-SVC	94.5%	114
	ν-SVC	94%	162
Sigmoid	C-SVC	93%	165
	ν-SVC	93%	162

Tab. 3 shows the classification accuracy of SVM using different kernels with support vectors. An SVM classifier yielded classification accuracy minimum of 92.5% of all kernels tested. Fig. 8 illustrated the comparison of C-SVC and ν-SVC models with different kernel functions of SVM. When comparing the classification accuracy, C-SVC model with polynomial kernel function is better than ν-SVC model with any kernel function for classification of a face milling tool. A confusion matrix of C-SVC model with polynomial kernel function is as shown in Tab. 4 which illustrates the classification of the face milling tool.

Table 4: C-SVC confusion matrix

a	**b**	**c**	**d**	
50	0	0	0	a-Healthy
0	50	0	0	b-Flank wear
0	0	45	5	c-Breakage
0	0	6	44	d- Chipping

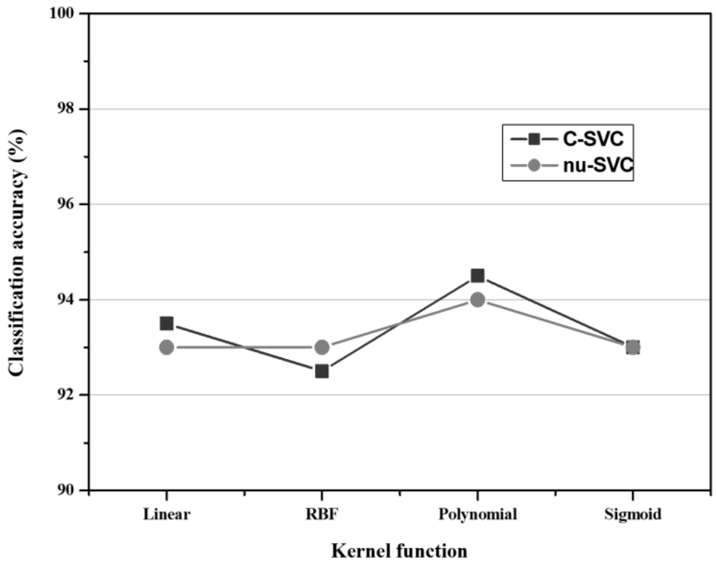


Figure 8: Comparison of C-SVC and *v*-SVC for face milling tool

Table 5: SVM parameters for DWT features

Test Parameter	Values
Test mode	10-fold cross validation
Total number of instances	200
Correctly classified instances	189 (94.5%)
Incorrectly classified instances	11 (5.5%)
Kernel function	Polynomial degree 3
Minimum error found	0.055

Tab. 4 shows the confusion matrix based on C-SVC model with polynomial kernel of SVM, diagonal elements represent the correctly classified instances. Here, 50 instances which belong to 'healthy' condition were correctly classified by the model as shown in the first element of the diagonal in the matrix. In the similar manner, all instances pertaining to 'flank wear' condition were classified correctly (second diagonal element). But in a third row, third column 45 instances indicate correctly classified as 'breakage', while third row, fourth column element indicates the condition of 'breakage' misclassified 5 instances as 'chipping'. Also in fourth row, third column 6 instances of 'chipping' condition were misclassified as 'breakage'. Tab. 5 shows the SVM parameters used with DWT features for classification of a face milling tool.

Table 6: Detailed accuracy classification of C-SVC

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
25%	0%	100%	100%	1	Healthy
25%	0%	100%	100%	1	Flank wear
22.5%	3%	88.24%	90%	0.8911	Breakage
22%	2.5%	89.80%	88%	0.8889	Chipping

Tab. 6 shows the detailed accuracy of the C-SVC model by class, in that true positive rate (TP rate) and false positive rate (FP rate) indicate the significance in judging the quality of the model. For good classification accuracy TP rate has to achieve 25% for each class, while the FP rate has to achieve 0%. For the given vibrational signals TP rate and the FP rate for healthy condition are about 25% and 0% respectively, which indicate all 50 instances are correctly classified. For breakage condition, TP rate is about 22.5% (correctly classification of 45 instances) and FP rate is about 3% (misclassification of 6 instances) and so on. SVM provides an excellent performance with high classification accuracy in fault diagnosis and machine condition monitoring [Widodo and Yang (2007)]. Here, out of 200 instances, 11 instances were misclassified by C-SVC model of SVM with classification accuracy about 94.5% of the given vibration signals.

5 Conclusions

In this paper, fault diagnosis of the face milling tool under healthy and fault (flank wear, chipping and breakage) conditions has been carried out using vibration signals. A set of discrete wavelet features was extracted from the vibration signals using the DWT technique. Salient features were selected among all extracted features using the decision tree technique. C-SVC and *v*-SVC models of SVM have been used to classify the different tool conditions using different kernel functions. Classification accuracies corresponding to different kernel functions have been compared. Based on the results obtained, C-SVC model with polynomial kernel of SVM provided a good classification accuracy of about 94.5% for the given experimental condition and workpiece of special steel alloy 42CrMo4. Hence, the combination of DWT features and C-SVC model of SVM can be recommended for the applications of fault diagnosis of face milling tool in the TCM system of machining processes.

DWT takes less computational time to extract features which are exist in the signal, but it decomposes only low frequency component of the signal. Decomposition at higher frequencies may provide useful information about the condition of the milling tool or any other system. Hence, further analysis can be carried out by considering the decomposition of high frequency component of the signal to improve the performance of the process or TCM system.

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