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Condition Monitoring Of Single Point Cutting Tool Using Arma Features And SVM Classifiers

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ABSTRACT

Single point cutting tool (SPCT) is one of the most significant machine tools which has been used in the present industrial era. Tool wear and tool life are the principle areas to be focused on. This paper manifests the condition monitoring which was done on SPCT in the interest of perfect surface finish. Closer and effective observations were made while in operation. The developed failure in the form of vibration signal had been revealed. From the vibration signals, ARMA features were extracted. The extracted features were then classified by using a supervised learning model called Support Vector Machine (SVM). A case study has been done for various types and range of problems in this particular tool, in a cross reference with the extracted feature set. The obtained results were compared. Unscheduled outages, machine performance optimization, repair time reduction and maintenance cost can be avoided with the help of this paper.

KEYWORDS: Vibration signals; Tool monitoring; ARMA features; SVM family; Fault Diagnosis.

I. INDRODUCTION

The demand to reduce production cost and to increase the quality of the product has driven manufacturers to monitor most of the operations. Excess chatter, tool wear out and breakage can be avoided by having a monitoring system. This is also important that the process must be absolutely reliable, and be able to operate continuously without any failure. Since customers are seeking for the products with tight specifications, it is important to produce work pieces to meet its specifications. This is the place where the lathe machine comes in handy. The main function of the lathe is machining and working of hard materials and to remove unwanted material from a work piece over the use of cutting tools. For the control of the machining process a tool condition monitoring system has become one among the fundamental requirements.

The operators in the industries will have a traditional sense of guessing the problem and breakage in machinery. This study investigates the use of vibration measurements on machine tools in order to identify the propagating wear of the selected tool. Feature extraction, feature classification and feature selection will be different stages of the process of conditioning monitoring. Many studies have been conducted on monitoring the abnormal cutting states of machine tools. At the time of installation of Single Point Cutting Tool, vibration signals were recorded. Since the operation is in its initial stage no wear and tear is there in the cutting tool. These recorded vibration signals will serve as the reference data set for further analysis. From each vibration signal, features were extracted using ARMA Features. The same data set which is considered as the reference will be used to cross check the fault data set for percentage of fault.

The study of literature in the field of machine tools revealed several efforts made by the scholars. Many studies have been conducted on monitoring the abnormal cutting states of machine tools. Silva R. G, Reuben R. L, et.al, (1998) used a variety of techniques used for fault diagnosis include, choice of the parameters to be captured, feature extraction, feature selection and feature classification. Many researchers have contributed toward condition monitoring studies that are computationally simple, yet effective and robust. Sick B (2002) made a comparison between different methods used to select and carryout simulation and a review was done in the research on both online and indirect tool monitoring. Franci Cus - Uros Zuperl (2010) explains Real-Time Cutting Tool Condition Monitoring in Milling and Daniel C. Volante (2011) about Condition Monitoring for Rotating Machinery. Condition monitoring has been established not only in machine tools but also in several parts of automobile. S. Babu Devasenapati, et.al, (2010) misfire in a four-stroke four-cylinder petrol engine has detected by sensing vibration signals with the help of a piezoelectric accelerometer. Decision tree was used for feature selection and classification. R. Jegadeeshwaran and V. Sugumaran (2013) have carried out a detailed study of piezoelectric transducer and data acquisition of sensed vibration signals from hydraulic breaks. C4.5 decision tree algorithm is also called as j48 algorithm was used to extract and select statistical features from vibration signals. The selected features affect more in the classification accuracy of the system and the paper has concluded with better classification accuracy. V. Muralidharan and V. Sugumaran (2013) have done fault diagnosis of mono-block centrifugal pump using wavelets and decision tree algorithm for feature extraction and classification respectively made a strong base for fault diagnosis in automobiles. Y.H. Pang, P.A. Flach, et.al, (2002) used decision tree for feature selection and the paper helped to obtain a clear view about different types of decision trees used in the WEKA software. V. Sugumaran, V. Muralidharan and K.I. Ramachandran (2008) used decision tree for feature selection and classification to find maximum classification accuracy. Information in the signal represented as features in the decision tree. Different conditions of the engine represented as leaves and the classification is done through the decision tree. The sequential branching process ending up with the leaves here is based on conditional probabilities associated with individual features. M. Amarnath, V. Sugumaran and Hemantha Kumar (2012) have used selected sound signal features instead of vibration signals, were then used for classification using C4.5 decision tree algorithm.

There are many techniques available for feature classification. SVM classifier is one among them. SVMs can produce accurate and robust classification results. M. Elangovan, K.I. Ramachandran and V. Sugumaran, (2010), used vibration signals as input data set and are successfully extracted from a single point carbide tool with the help of statistical and histogram features. Here the classification was done by using bayes classifier and while comparing statistical features yield more accurate results than the histogram features in the data set that was obtained. V. Sugumaran and K.I. Ramachandran (2011) have done a comparative study on effect of number of features on classification accuracy of roller bearing faults using SVM and PSVM and hence revealed the efficiency of SVM classifier. M. Elangovan, V. Sugumaran, et.al, (2011) have done another research on single point cutting tool using SVM as the kernel function had referred in the same vibration signal. In the proposed system ARMA features and SVM family has been used for the vibration feature extraction and classification respectively. M. Elangovan, et.al, (2011), Richard J. Malak, et.al, (2010), Luke Bornn, et.al, (2013) has been reported the SVM classifier and its efficiency. R. Jegadeeshwaran and V. Sugumaran (2013), have helped in understanding different kernel functions in SVM classifier. c-SVC and nu-SVC are two differant models of support vector machine (SVM) with four kernel functions for classification. A comparison made between c-SVC and nu-SVC results in finding better classification accuracy. V. Muralidharan and V. Sugumaran (2013) used MSVM which is another model of SVM classifier. The statistical features are extracted from vibration signals and classified successfully using MSVM. Babu Devasenapati S, Ramachandran K.I and Sugumaran V (2010) made a solid study on classification accuracy of SVM when using statistical and histogram features for misfire detection in a spark ignition engine.

The above literature survey has helped to gain good knowledge and understanding of existing techniques. Based on the knowledge and information, An attempt has been made in this paper to combine and test a different set of combination of techniques used in fault diagnosis. In this attempt a single point cutting tool was used as subject element. The feature extraction has done using ARMA model. Feature classification was done using Support Vector Machine (SVM).

II. METHODOLOGY

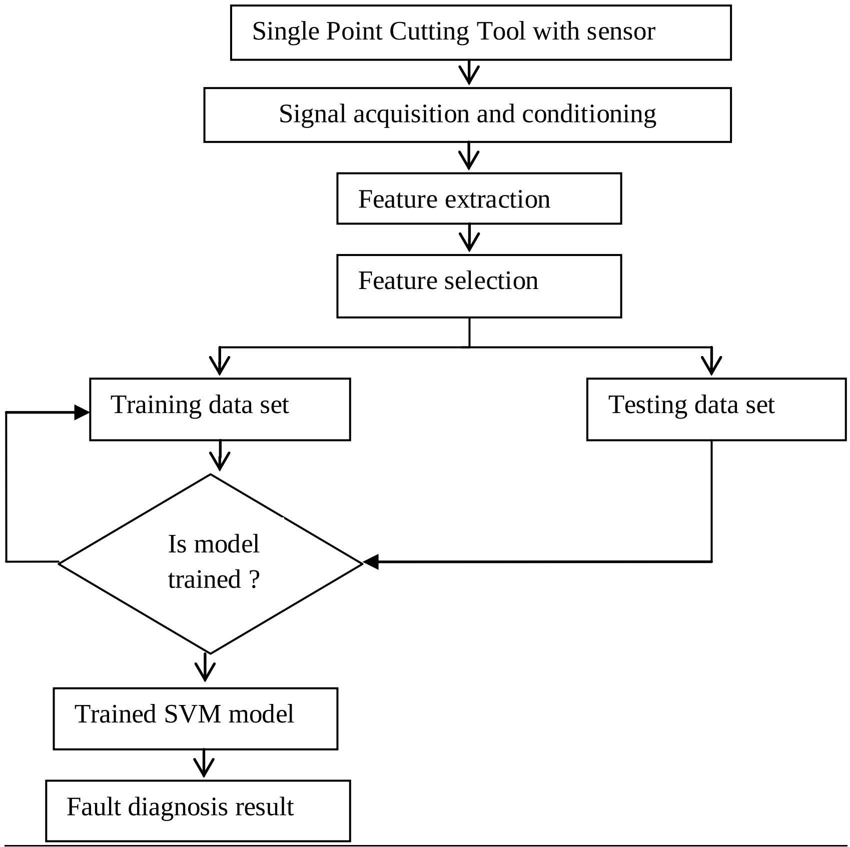

Fig. 1. Methodology

III. EXPERIMENTAL STUDIES

The experimental studies are made through an experimental set-up and the procedure followed for experiment also described in the following subsections.

A. Experimental set-up

The experimental set-up is shown in Fig. 2. The experimantal unit consists a CNC turning center (ACE Micromatic – Classic 20T), a piezoelectric accelerometer, a signal acquisition and conditioning unit (DAC) and a computer to record the signals. A chuck holds a 20mm diameter mild steel shaft and a tool post consists of a single point carbide tipped cutting tool. The CNC machine was set with a 0.8mm nose radius of tool, 0.1mm/s feed, 0.5mm depth of cut and 600 rpm spindle speed. The tool holder has the piezoelectric accelerometer mounted on it using adhesive. There was a charge amplifier and an analog to digital convertor through which the signal will flow in the signal conditioning unit to which the accelerometer is connected. Through the USB the vibration signals from the signal conditioning unit were fed to the computer. Recording the signals to the computer secondary memory was done using RT-pro series software. The statistical features were then extracted from the red and processed data or signals.

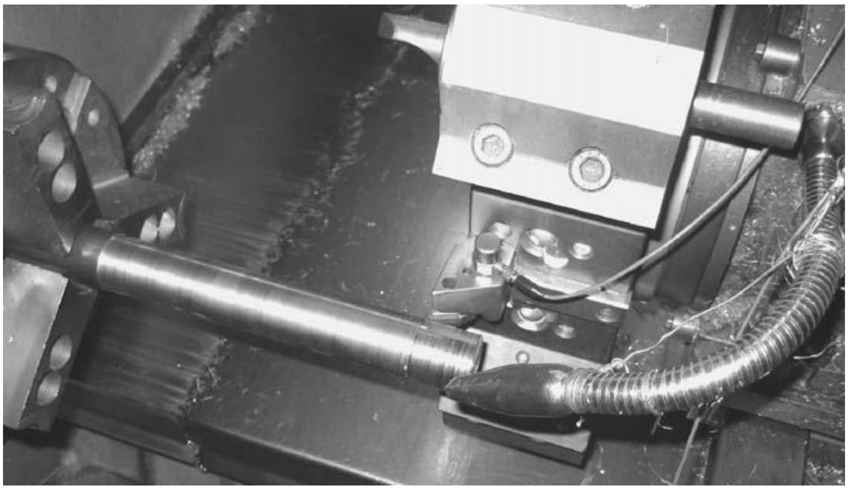

Fig. 2. Experimental set-up.

B. Experimental procedure

1. Acquisition of baseline signal

The tool post was fixed with an unused carbide tool tip (TNMG160408). With the help of adhesive an accelerometer was fixed to the tool holder. The sampling frequency of 24 kHz, sampling length of 8192, type of signal etc., were set as signal acquisition parameters. A highest frequency of 12 kHz was recorded and the sampling frequency of 12 kHz was recorded and the sampling frequency was chosen to be 24kHz based as based on the nyquist criterion, the sampling frequency should be twice that of the measured maximum frequency. The 20mm rod which underwent oxidation was smoothened by its surface by clamping it to the live center and carrying out a rough turning. The initial random variation which is typical in any measurement was avoided by purposefully ignoring the first few signals.

2. Fault simulation

As pointed out earlier, fault conditions considered in this study are the following.

1. The tool tip in less blunt (0.3 mm) condition – (tool blunt low).
2. The tool tip in more pronounced blunt (0.6 mm) condition – (tool blunt high).
3. The condition, where the tool tip was loosened by a one twelfth a revolution (tool tip loose).

To create bluntness in the tool tip, the following procedure was followed. Parallel to tangent of nose radius a reference line was marked on the fresh tool tip. Then the distance between reference line and highest point on the nose radius has been measured and recorded. The nose of the tip was ground by a small distance by using a tool and cutter grinder. The bluntness was arrived by taking the difference of distance between the edge and reference line. The same procedure was carried out using various tools.

3. Acquisition of signal under fault condition.

The turning process was allowed to stabilize before the vibration signals are picked up from the piezo electric accelerometer. The sampling frequency of 24KHz and sampling length of 8192 has been kept for all conditions. The sample length of 8192 which in turn gives 2^{13} which is around 10,000 readings. They show time domain plots of vibration acceleration of a good tool tip (new tool tip without any fault), tool tip with less blunt condition, tool tip with high blunt condition, and tool tip being slightly loosened.

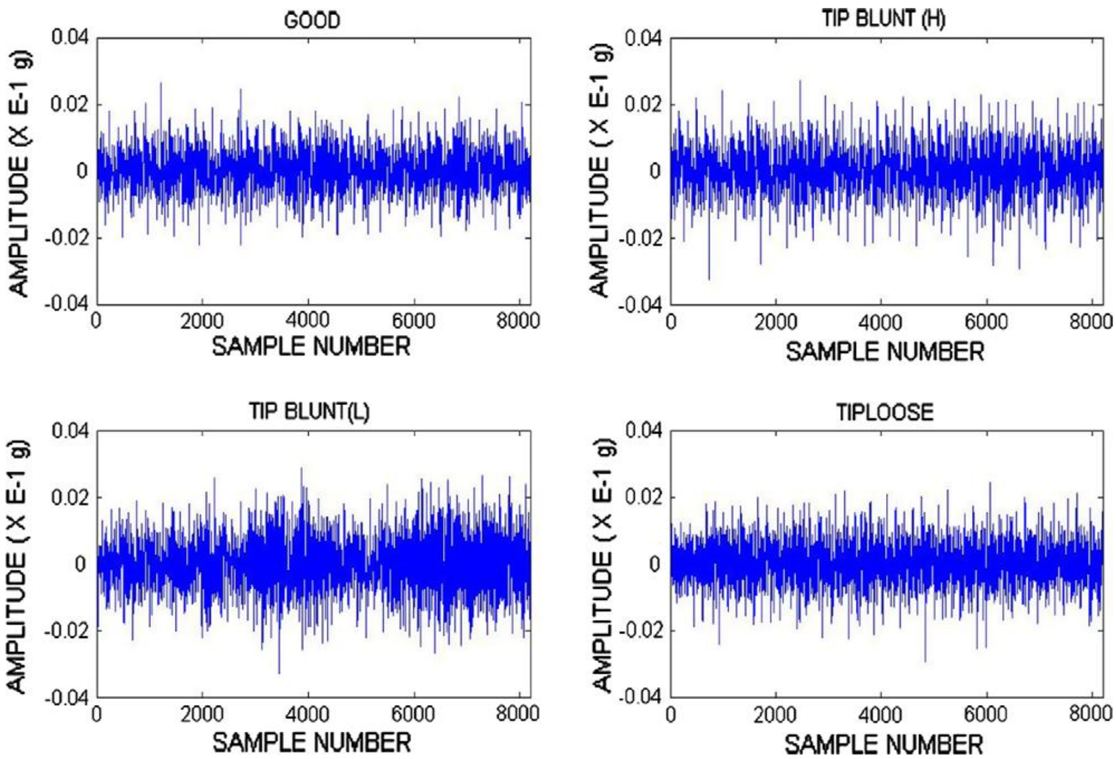

Fig. 3. Plot of time domain signals.

IV. PHASES OF CONDITION MONITORING

A. Feature Extraction

The vibration signals collected from the raw material will be undergoing a process of condition monitoring through various process of data analysis. Condition monitoring makes the predictive maintenance comes true. In this particular section ARMA features were extracted from the acquired vibration signals through data analysis. Mean, median - average, kurtosis - sharpness of the peak of frequency-distribution of signal, skewness - measure of the asymmetry of mean, mode - repeating value, variance - spread data, standard deviation - difference from the mean value are the selected attributes for the feature extraction. ARMA model which is a convenient tool in analyzing time series values and express output in terms of two components, namely Auto Regressive and Moving Average polynomials. ARMA models have been fitted to history response data from machines in undamaged states in order to create features for statistical process analysis and the ARMA coefficients are fed to the classifier.

B. Feature Selection

Feature selection is a method for replacing a complex classifier using all features with a simpler one using a subset of the features. Feature selection is the process of selecting a subset of the terms occurring in the training set and using only this subset as features. Feature selection serves two main purposes. First, it makes training and applying a classifier more efficient by decreasing the size of the effective features.

Feature selection process was done using the decision tree algorithm called J48. The decision tree represents a detailed information regarding all the parameters, into given conditions. The percentage of accuracy of a particular tree for each set of data will also be given. A decision tree can be considered as a good one if the percentage of accuracy is relatively more with less parameters than that of a tree which has a slightly more accuracy percentage with more parameters. Thus the number of parameters will always be observed to be less. After extraction of features, decision tree for each mean order of above mentioned functions where derived and decision tree for mean order 9 with least number of feature was selected from the following decision tree shown in Fig.3. Hence mean order 9 is used in forthcoming processes.

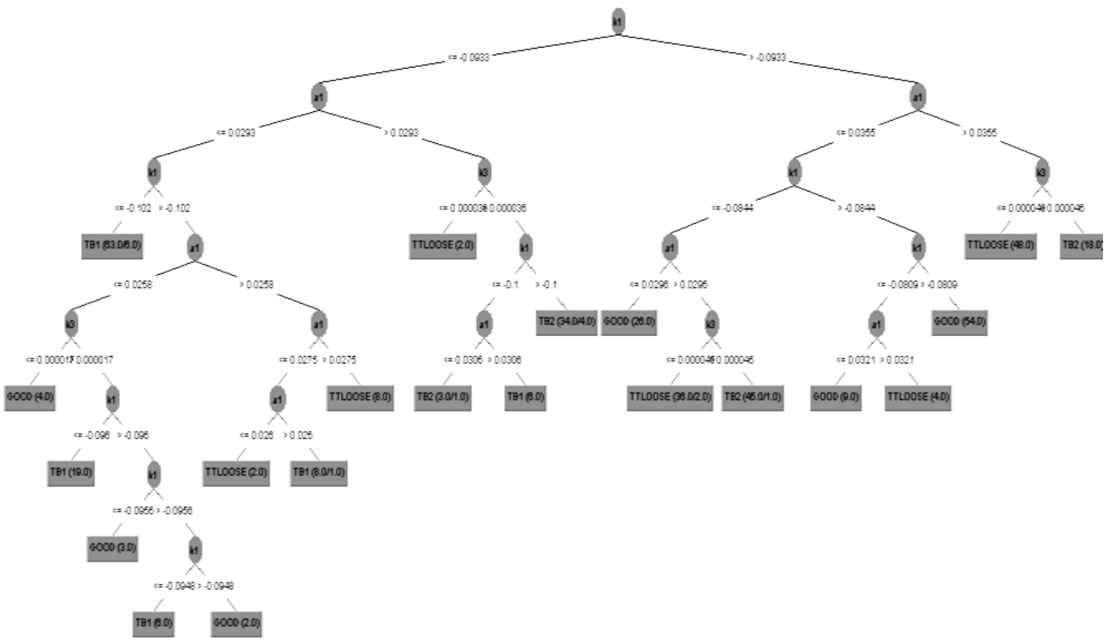

Fig. 4. Decision Tree for ARMA Features.

C. Feature classification

Support Vector Machine

Support Vector Machines (SVM) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. [13] the data points *P1, P2* and *P5* belonging to *A-* are support vectors (See Fig.4), however *P6, P7* are not. Same facts hold good for class *A+*. In theory these points play a vital role and hence the name 'Support Vector Machines'. Here, 'machine', means an algorithm. In the formulation, $'A'$ is an $m \times n$ matrix whose elements belong to real space, *'D'* is an $m \times 1$ matrix representing class label (+1 and –1); '*e*' is a vector of ones and *'v'* is a control parameter that defines the weight of error minimization and bounding plane separation in the objective function. $'w'$ is orientation parameter and $'\gamma'$ is location parameter (location relative to origin) of separating hyper plane. With these notations,

$$\min\ (w, \gamma, y) \in R^{n+1+m^{v\, e'\, y\, +\, 1/2\, w' w}}$$

subjected to

$$D(Aw - e\gamma) + y \geq e$$
$$y \geq 0$$

where,

$$A \in R^{m \times n}, D \in \{-1, +1\}^{m \times 1}, e = 1^{m \times 1}$$

The smaller the size of the support vector set, more general the above result. The generalization is independent of the dimension of the problem. In case such a hyper-plane is not possible, the next best is to minimize the number of misclassifications at the same time maximizing the margin with respect to the correctly classified features.

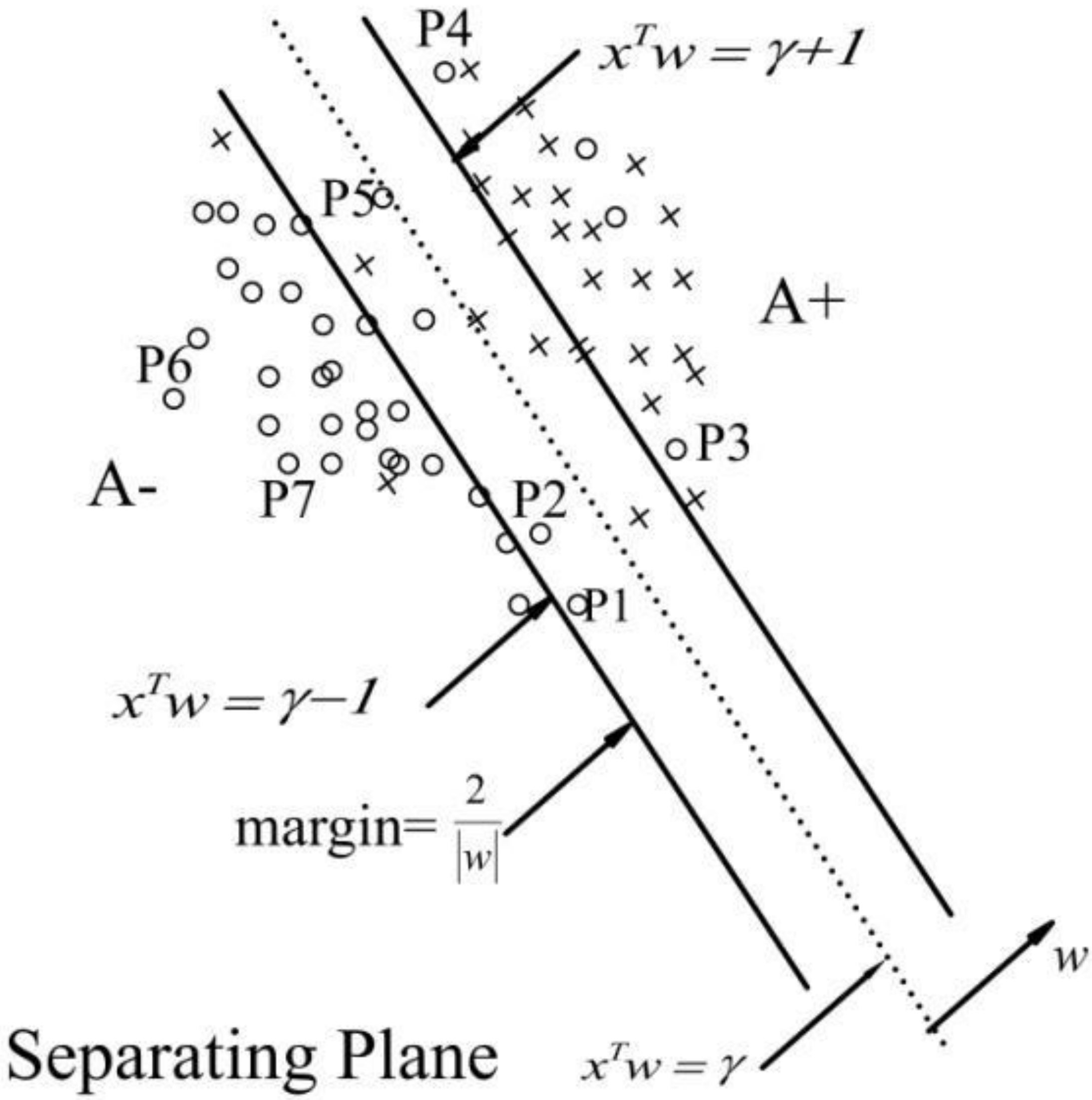

Fig. 5. Standard SVM classifier

The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output. In this paper, the combination of a1+k1+k3+condition has been taken since this condition alone is producing the output of 88% where the rest combination produce the very less result. By taking the condition along with the parameters, Support Vector Machine (SVM) has been derived. In the SVM, there are two types of models which were used much in the analysis of the overall accuracy they are Classification and Regression. Also there are two types of classification analysis and regression analysis, they are as follows.

Table 1: Types of SVM model

Classification	Regression
C-SVC	Epsilon-SVR
Nu-SVC	Nu-SVR

Under the two types of the classification, four types of kernel functions are considered; they are Linear, Polynomial, Sigmoid, Radial Basis Function (RBF). Kernal function polynomial has certain degree levels where it is increased form the degree 1 to 3. In this paper, all the three Levels (i.e.) Degrees are considered for the polynomial function performance analysis. Here the highest accuracies from the C-SVC and the Nu-SVC values are compared. The C-SVC are given as Regularized Support Vector Classification which are used as a standard algorithm in the SVM. The Nu-SVC are nothing but the Automatically Regularized Support Vector Classification which are used to find the output of the overall accuracy automatically.

V. RESULTS AND DISCUSSIONS

The fault diagnosis of Single Point Cutting Tool was taken up. Tool monitoring was carried out with ARMA feature and SVM combination. The highest parameters obtained after feature selection are classified using Support Vector Machine (SVM). Classification was obtained using "Ten Fold Cross Validation" method. In this method, the values are been tested with the help of algorithm and also they are obtained in the form of matrix form. The maximum value obtained in the C-SVC and Nu-SVC with the kernel functions has been given in Table 2: where the values of both the training data and the validation data for which the best accuracy percentage has been carried out.

Table 2: Classification efficiency for various kernels.

SVM Classifiers	Kernel Functions	Training data	Validation data
C-SVC	Linear	94.25%	93.25%
	RBF	97.50%	**95.75%**
	Sigmoid	93.75%	93.75%
	Polynomial 1^0	94.25%	93.00%
	Polynomial 2^0	96.75%	95.50%
	Polynomial 3^0	96.75%	95.50%
Nu-SVC	Linear	93.75%	94.00%
	RBF	95.50%	94.50%
	Sigmoid	94.50%	94.25%
	Polynomial 1^0	92.50%	91.75%
	Polynomial 2^0	97.25%	96.00%
	Polynomial 3^0	96.75%	**96.50%**

A. Feature Classification Using C-SVC.

The C-SVM was trained using Linear, RBF(Radial Basis Function), sigmoid and Polynomial kernels. For different kernel functions, the classification accuracy of C - SVM for statistical features is presented in Table 1. Among all other kernel functions, RBF for C – SVM gives better classification accuracy (97.50%). The confusion matrix for the particular RBF function is also given in Fig.5.

B. Feature Classification Using Nu-SVC.

The Nu-SVM was trained using Linear, RBF(Radial Basis Function), sigmoid and Polynomial kernels. Polynomial 2^0 was trained with maximum accuracy. Kernels are compared with the help of accuracy while they are used for classification. For different kernel functions, the classification accuracy of Nu - SVM for statistical features has been presented in Table 2. Here polynomial 2^0 and polynomial 3^0 are trained with (97.25%) and (96.75%) accuracy respectively. While studying the validation data polynomial 2^0 is giving (96.00%) and polynomial 3^0 is giving (96.50%), Which reveals that polynomial 3^0 is more closer to the expected accuracy than polynomial 2^0. Among all other kernel functions, the validation result is Polynomial 3^0 gives better classification accuracy for C – SVM (96.50%). The confusion matrix for the particular Polynomial 3^0 function is given in Fig.6.

-------- Training Data --------

Actual : Category:	-------Predicted Category------ GOOD	TB1	TB2	TTLOOSE
GOOD:	100	0	0	0
TB1:	0	92	8	0
TB2:	0	10	90	0
TTLOOSE:	0	4	1	95

-------- Validation Data --------

Actual : Category:	-------Predicted Category------ GOOD	TB1	TB2	TTLOOSE
GOOD:	100	0	0	0
TB1:	0	91	9	0
TB2:	0	12	88	0
TTLOOSE:	0	4	2	94

Fig.5. Confusion matrix of training and validation data for C-SVC (RBF)

-------- Training Data --------

Actual Category:	GOOD	TB1	TB2	TTLOOSE
GOOD:	100	0	0	0
TB1:	0	98	2	0
TB2:	0	5	95	0
TTLOOSE:	0	5	1	94

-------- Validation Data --------

Actual Category:	GOOD	TB1	TB2	TTLOOSE
GOOD:	100	0	0	0
TB1:	0	98	1	1
TB2:	0	7	93	0
TTLOOSE:	0	4	1	95

Fig.6. Confusion matrix of training and validation data for Nu-SVC (Polynomial 3^0)

Overall the study of classification of tool condition using SVM can be summarised as,

- Comparison of the linear, radial basis function and sigmoidal results.
- Comparison of polynomial kernels of different degree.
- Comparison between C-SVC and Nu-SVC kernels

Comparison of classification accuracy of training data and validation data of both C-SVC and Nu-SVC classifiers are represented graphically in Fig.8 and Fig.9 respectively.

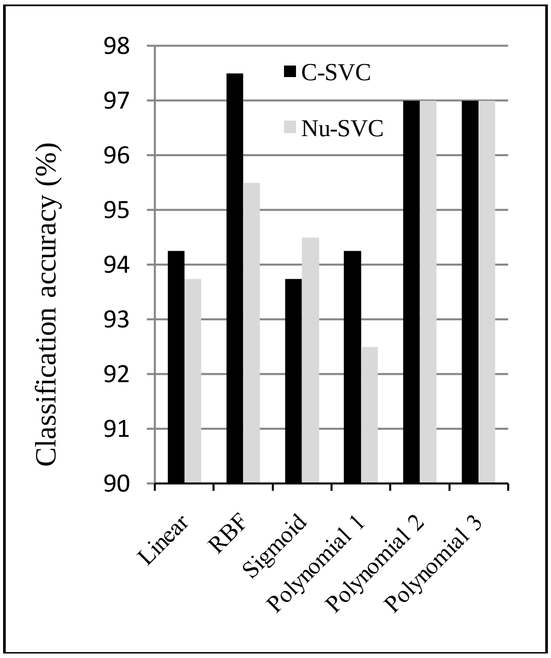

Fig.8. Comparison of classification accuracy of training data

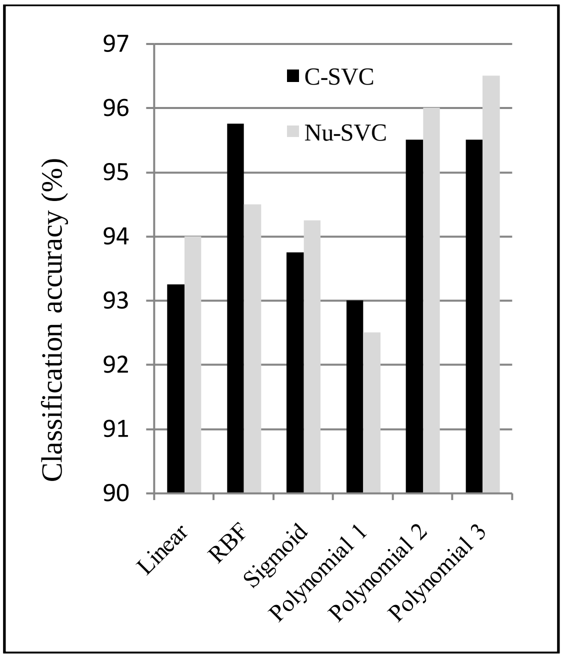

Fig.9. Comparisson of classification accuracy of validation data

Table 3: Run Time Analysis

Kernal Functions	Run time (s)	
	C-SVC	Nu-SVC
Linear	1.23	1.17
RBF	7.37	3.87
Sigmoid	56.93	36.75
Polynomial 1^0	64.16	19.69
Polynomial 2^0	185.96	131.84
Polynomial 3^0	878.33	705.14

The confusion matrix was obtained for both C-SVC and Nu-SVC. Table 3 contains the time taken by each kernal functions to run under both C-SVC and Nu-SVC. While analyzing, from kernal function linear to polynomial 3^0 the run time is gradually increasing. Performance always depends on time, means less time for high performance. According to that kernal functions, linear and RBF are showing high performance. After undergoing a detailed study through the accuracies which had been obtained for each kernal functions and the performance time by using C-SVC and Nu-SVC algorithms, Nu-SVC is giving better accuracy compared to C-SVC.

VI. CONCLUSION

Condition monitoring of a single point cutting tool was carried out using vibration signals and the ARMA features were extracted. Each of them was classified using SVM classifier and the superior feature–classifier combination was found. From this research, the condition monitoring was done for Single Point Cutting Tool, classification accuracy was obtained from the two different types of classifiers such as C-SVC and Nu-SVC. It is found that the C-SVC classifier with the kernel function of Radial Basis Function (RBF) and Nu-SVC classifier with the kernel function of Polynomial third degree gives a better result. Comparison of C-SVC and Nu-SVC based on its run time reveals that Nu-SVC is more efficient since time taken for the analysis is less. Hence by comparing the results of C-SVC and Nu-SVC with all the kernel functions, the Nu-SVC with Polynomial 3^0 kernel function performs better for finding the accuracy of tool monitoring.

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