ISSN: 0974-2115
www.jchps.com Journal of Chemical and Pharmaceutical Sciences

Tool wear monitoring using the fusion of vibration signals and digital image

Krishna Pradeep GV*, Saimurugan M, Ravi Kumar S
Mechanical Engineering Department, Amrita Vishwa Vidyapeetham, Coimbatore, India
***Corresponding author: E-Mail: gvkpradeep@yahoo.com**

ABSTRACT

Tool wear monitoring is an indispensable peremptorily of advanced manufacturing in order to evolve an automated unmanned production. Continuously machining with a worn or impaired tool will result in damage to the work piece. This difficulty becomes more important in subsidiary machining processes like milling which the tool has regularly passed a lot of machining processes and any destruction to work piece at these level consequences in more production losses. In this work, vibration signals in milling process are recorded and examined carefully in order to detect tool wear. The online acquiring of machined surface images has been done at intervals and those captured periodic texture of machined surface images are analysed for detection of tool wear. The vibration signals and the digital images are analysed using data mining techniques, decision tree to classify the tool wear. Further, the effectiveness of fusion of sensory data from the CCD camera (Image analysis) and an accelerometer (Vibration analysis) in tool wear prediction is checked and compared.

KEY WORDS: Tool Condition Monitoring, TCM, Milling, Fusion, Decision tree, Tool condition diagnosis.

1. INTRODUCTION

Tool condition monitoring (TCM) is an important factor in the unintended machining process. The era in the field of machining process, the ultimate aim of this process is to have the good surface finish with high quality. After some predominant intervals of time the tool will wear and it leads to effect in machining process. Unexpected break down in the machine or tool, it leads to loss in productivity and increase in maintenance costs. The main aim of the TCM is to increase the production and compete to maximize the tool life, minimizing downtime, reducing the scrap and preventing damage. Many researchers have conducted on monitoring of fault and abnormal cutting states of machine tools. Continuous monitoring system has been developed for the identification of the fault. Tool wear monitoring has been classified in to two categories i.e. direct and indirect methods. In the direct method, optical devices are used to determine the wear land. In the indirect method, acquisition of process variables such as cutting force, temperature, acoustic emission, vibration and surface roughness. From the above variables, vibration gives the best effectiveness for rotating elements. Vibration monitoring is mainly used to identify the tool condition, surface quality, and surface roughness in machining process. The accelerometer is fixed at the spindle and the output signal is connected to the Vib pilot SO analyzer for acquiring the vibration signals. Image acquisition is the important factor in machine vision. In TCM system, the work piece image is captured by high resolution digital camera and it is processed by using image processing techniques. In general, by seeing any product we can identify the quality of surface and detect any major faults. The surface roughness parameters and other hidden information from the digital image are processed by many techniques one of them is GLCM (grey level co-occurrence matrix) technique, which helps to find the Texture analysis of images. The past researchers have monitored either vibration data or capturing of machined surface image. The current research in the TCM is a multisensory approach which is known as sensor fusion, sensor integration, and sensor synthesis. The present work gives the advances in the fusion of the signals, i.e., vibration with digital image. Fusion of data is differentiated in three aspects i.e. signal level, feature level, symbol level. Feature level fusion indicates that signal attributes are fuse to have estimation of certain signal characteristics. Time domain vibration data's are obtained and it consists for huge data sets, so it is impossible to detect the fault from a large data. Hence feature extraction has to be done, where statistical features are extracted from obtained vibration signal and same procedure is followed also for processed image. Statistical features have prior used in condition monitoring technique. For feature classification, a machine learning algorithm decision tree is used for building a model from statistical feature data inputs in order to make decisions. Decision tree is used for classification function which holds the dependent attribute given the values of the independent attributes. Decision tree which enhance the hidden structural information enclose in the acquired vibration data and digital image. This paper illustrates the use of J48 algorithm which predominantly to select best features from the given extracted features same as used to diagnose the tool condition. In this work, a mild steel plate of dimension 80x150mm is clamped on the chuck. A face milling operation is carried out to remove the top surface of the plate for 12 different test conditions to monitor its vibration and surface pattern. A tri-axial piezo electric accelerometer is fixed on the spindle where all the cutting forces will act on it. The subsequent digital image is also captured from high resolution camera. Statistical features are extracted for both the vibration signal and machined surface digital image and it is passed to decision tree for feature classification. The methodology chart is shown in fig 1.

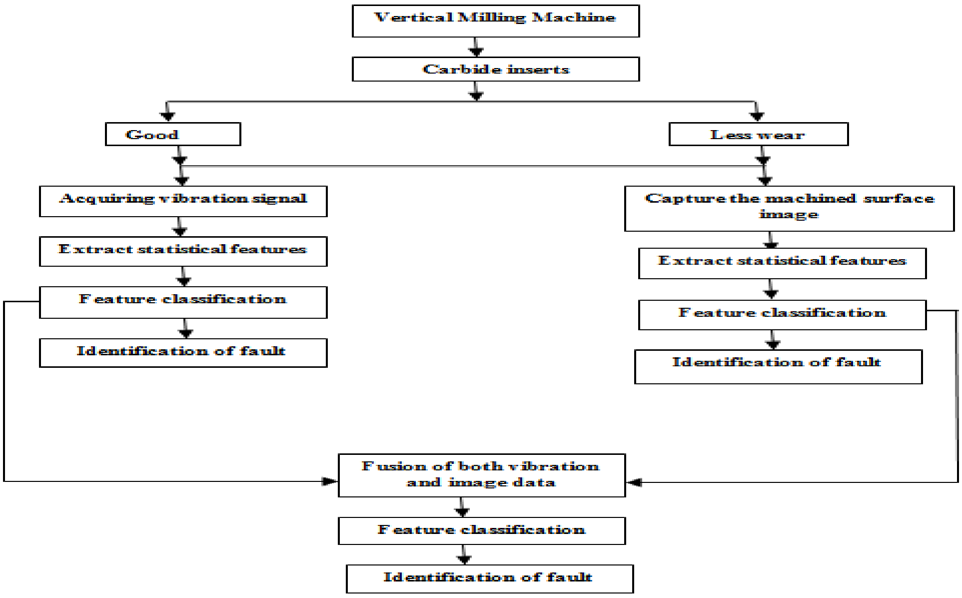

Fig.1.Methodology Chart

2. MATERIALS AND METHODS

Experimental set up for acquisition of vibration signal: The experimental setup consists of vertical milling machine (bharat fritz warner ltd), a Piezo electric accelerometer, SO analyzer and computer to record the signals. A mild steel plate of thickness 1 inch is fixed on the vice and a multipoint cutting tool-titanium coated carbide inserts are fixed on the tool post. The tri-axial piezo electric accelerometer is fixed on the head of spindle by using additive glue. The output of the accelerometer is connected to the signal conditioning unit i.e. SO analyzer DAQ. Fig 2 shows the set up for accelerometer.

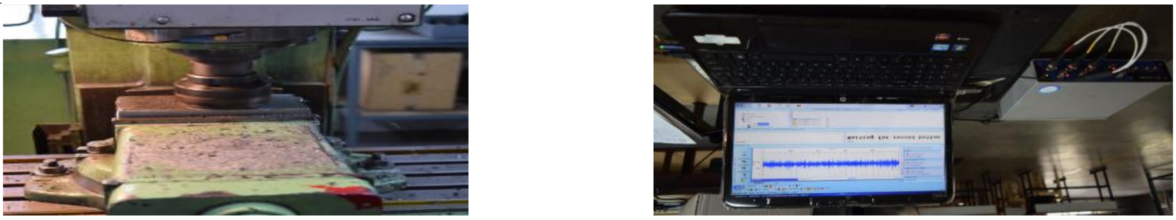

Fig.2.Experimental set up having accelerometer & DAQ setup

Set up for equivalent Lighting system for acquiring image: Lighting system is the most important factor for getting a good image in the image processing. A good lighting system can collect hidden information in the work piece. For this many researchers are working for setting the proper lighting system in tool condition monitoring. For the lighting system, the previous authors are used two flood lights arranged such that there is proper illumination of light in all directions. Lighting set up will be vary for different applications i.e., capturing the tool wear image or machined surface image. In this work machined surface image is captured for identifying the class of wear i.e. good or fault. For this a high resolution camera, Nikon DSLR is used for capturing the machined surface. The machined work piece is placed at the closed box such that it cannot reflect the outside light. Camera is fixed at constant position by using tripod; the focus of the camera is adjusted such that it covers the entire work piece. There are two led light lamps placed on the side of the box, such that the work piece is covered with constant illumination in all directions, then the image is captured. Figure 3 shows the set up for capturing digital image of machined surface.

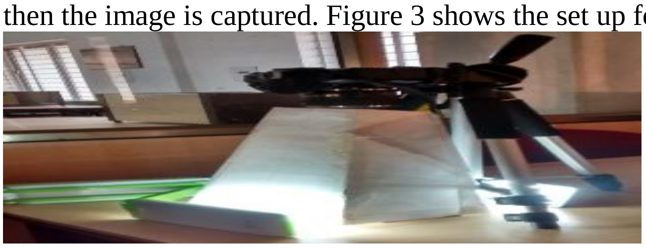

Fig.3. Setup for acquiring image

Fig.4. Fault creation using surface grinding machine

Fault creation: The surface grinding process is used for creating the bluntness in milling insert. Good 5 milling inserts are taken and it is fixed in milling cutter. Dial indicator is used to check height uniformity in all the inserts. Then the cutter is placed on the surface grinding machine and it is ground for 1mm. The fault is measured by using video measuring machine. The measurement values of fault are shown in Table 1. Figure 4 shows the fault creation using surface grinding machine. The two tool conditions are as follows,

a) The insert tip is in good condition.
b) The insert tip is in blunt i.e. 1.0mm

Acquisition of vibration signal: To acquire the vibration signal, an un used milling inserts (Titanium coated carbide inserts) are placed in the cutter. Totally 2 fault classes were assigned, each fault class contains 12 operating conditions by varying speed, feed and depth of cut as shown in Table 2. So, totally 24 operating conditions were obtained by combining all 2 fault classes.

Table.1.Bluntness of measured values

S.no	Measured bluntness(mm)
1	1.1
2	1.0
3	1.2
4	0.9
5	0.8

Triaxial accelerometer is fixed on the spindle head and the acquired signal is send to the DAQ card. For acquiring signals, initial parameters of sampling length (200) seconds, sampling frequency (8192) kHz were fixed. The time domain vibration signals are acquired and data's are saved.

Table.2.Cutting conditions

Speed (rpm)	Feed (mm/min)	Depth of Cut (mm)	Speed (rpm)	Feed (mm/min)	Depth of Cut (mm)
250	25	0.20	250	25	0.40
250	50	0.20	250	50	0.40
500	25	0.20	500	25	0.40
500	50	0.20	500	50	0.40
710	25	0.20	710	25	0.40
710	50	0.20	710	50	0.40

Acquiring digital image from machined surface: The following procedure is done after acquiring the vibration signal for particular cutting condition. The work piece is taken from the vice and it is placed on the table, such that equal illumination of ambient light is maintained constantly for all the cutting conditions. In this work, a high resolution camera with 6000x4000 image size was fixed such that the quality of image is high and DPI (Dots per inch) will be decrease. The focus of camera is adjusted such that it covers the entire work piece. Camera is fixed in the tripod at certain height and the work piece is kept inside the closed box. Two LED light lamps are arranged at the outside of the closed box such that the light intensity is equal in all directions; this arrangement is common for all tool conditions. The captured image is processed by using image processing technique and statistical features are extracted by using mat lab.

Feature extraction: After acquiring the vibration signal, the features are extracted and it is called as dimensionality reduction technique. The data acquired is too large & all the data's are not relevant, so feature extraction technique is employed to reduce the number of features without any loss in information. This extraction process is followed for all conditions that are tool tip is in good condition and tool tip is in bluntness, by using matlab. Similarly, the subsequent machined surface image is processed by using image processing technique and features are extracted. Time domain statistical features extracted are mean, sum, median, min, max, mode, standard deviation, variance, kurtosis and skewness.

Feature classification: Decision tree is a classifier in the form of a tree structure. It represents the information such that with a data set of predictors or independent variables and a data of targets or dependent variables. The decision tree has more advantages which follow:
a) Decision tree is easy to understand and it is very user friendly.
b) There are no particular assumptions about nature of data.
c) Decision trees can classify both the categorical and numerical data, but output must be categorical.
d) It gives a clear identification of which fields are most important for classification.

Fusion of vibration signal and digital image: The main aim of the work is to fuse the featured level data of vibration signal and digital image. The current research in TCM is going on the fusion of multiple sensors i.e. temperature, vibration etc, in the era of machining process. In obtained features from the individual vibration data and digital image is fused. The fusion of both the vibration and digital image gave the best efficiency. The best classification efficiency is taken for the individual vibration signal or digital image or fusion of both the signals.

3. RESULTS AND DISCUSSIONS

As per the tool conditions, the experiments are done on the good tip and less blunt tip based on the cutting conditions i.e. speed, feed and depth of cut. The classification is proceeded by training and testing of the extracted features. The obtained time domain features will be saved and data is extracted with the help of mat lab. These extracted data contains desperate values for all experimental conditions. Decision tree is used for the classification, the confusion matrix for 250 rpm speed, 50 feed and 0.4 depth of cut is shown in Table 3.

Table.3.Confusion matrix for vibration signal

A	B	Classified as
99	1	A=GT_250_50_0.4
2	98	B=FT_250_50_0.4

The confusion matrix obtained from the decision tree which is taken as sample values are shown in Table 3. In condition A, out of 100 data sets 99 data's are correctly classified in class A and 1 data as misclassified has class B. In condition B, out of 100 data 98 data's are correctly classified in class B and 2 data's are misclassified has class A. Similarly for remaining tool conditions, the features are extracted and the overall efficiencies of the vibration signal have done. Table 4 shows the overall efficiencies vibration signal obtained from decision tree for all tool conditions.

Table.4.Classification efficiencies for vibrational signal

Conditions	Efficiency (%)	Conditions	Efficiency (%)
250_25_0.2	99	500_25_0.4	95.5
250_50_0.2	99.5	500_50_0.4	97
250_25_0.4	99.2	710_25_0.2	99.5
250_50_0.4	98.5	710_50_0.2	99.5
500_25_0.2	96.5	710_25_0.4	97.5
500_50_0.2	92	710_50_0.4	98

The mean efficiency of vibration signal is 97.64%. After acquiring the vibration signals of the particular tool condition, subsequent machined surface image is captured by using the camera. The image is processed by using imaging processing technique and statistical features are extracted. These extracted features will vary for different cutting conditions. Decision tree is used for the classification, the confusion matrix for 250 rpm speed, 50 feed and 0.4 depth of cut is shown in Table 5.

Table.5.Confusion matrix for digital image

A	B	Classified as
94	6	A=gt_250_50_0.4
4	96	B=ft_250_50_0.4

The confusion matrix obtained from the decision tree which is taken as sample values are shown in Table 5. In condition A, out of 100 data 94 data's are correctly classified in class A and 6 data's are misclassified has class B. In condition B, out of 100 data 96 data's are correctly classified in class B and 4 data's are misclassified as class A. Similarly for remaining tool conditions, the features are extracted and the overall efficiencies of the digital image have done. Table 6 shows the overall efficiencies digital image obtained from decision tree for all tool conditions.

Table.6.Classification efficiencies for digital image

Conditions	Efficiency (%)	Conditions	Efficiency (%)
250_25_0.2	100	500_25_0.4	84
250_50_0.2	99.5	500_50_0.4	82
250_25_0.4	83.5	710_25_0.2	92.5
250_50_0.4	95	710_50_0.2	72.5
500_25_0.2	92.5	710_25_0.4	78.5
500_50_0.2	87	710_50_0.4	88

The mean efficiency of machined surface image is 88.14%. The results are showed for the individual vibration signal and digital image. Now, both the vibration and digital image signals are fused and the confusion matrix for 250 rpm speed, 50 feed and 0.4 depth of cut is shown in Table 7.

Table.7.Confusion matrix for fusion of signals

A	B	Classified as
99	1	A=GT_250_50_0.4
2	98	B=FT_250_50_0.4

The best classification efficiency is obtained while fusing both the signals. The confusion matrix obtained from the decision tree which is taken as sample values are shown in Table 7. In condition A, out of 100 data 99 data's are correctly classified in class A and 1 data as misclassified has class B. In condition B, out of 100 data 98 data's are correctly classified in class B and 2 data's are misclassified has class A. Similarly for remaining tool conditions, the features are extracted and the overall efficiencies of the fusion of both signals have done. Table 8 shows the overall efficiencies of fusion of both signals.

Table.8.Classification efficiencies for fusion of signals

Conditions	Efficiency (%)	Conditions	Efficiency (%)
250_25_0.2	100	500_25_0.4	94
250_50_0.2	99.5	500_50_0.4	97.5
250_25_0.4	99.5	710_25_0.2	99.5
250_50_0.4	98.5	710_50_0.2	99.5
500_25_0.2	97.5	710_25_0.4	99
500_50_0.2	95.2	710_50_0.4	96.5

The best classification efficiency is obtained while fusing both the signals. The mean efficiency of fused signal is 98.01%. Table 9 shows the efficiency of the all Vibration, digital image and fused data. Fused data shows a slightly higher efficiency over vibration and it can be used for the fault identification.

Table.9.Classification efficiencies for fusion of signals

Type of signal	Mean Efficiency (%)
Vibration	97.64
Digital image	88.14
Fusion	98.01

4. CONCLUSIONS

Tool wear monitoring is important in the machining process for getting a good surface finish and high accuracy. This paper presents the acquisition of vibration signal and capturing the machined surface image for different tool condition. The statistical features are extracted for both vibration and digital image. The results of classification efficiencies of both the signals have shown. Main aim of this paper is to fuse both the vibration and image signals, it results in higher efficiency over individual once. Importance of decision tree (J48 algorithm) classifier and their advantages are entitled.

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