Tool Condition Monitoring-A Review

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Abstract
The condition of the tool is the most significant factor in the manufacture of a quality product. Manufacturing a product involves different cutting tools, and the tool will wear out during product manufacturing. Using a worn-out tool would result in the formation of the defective product. Thus monitoring of cutting tools assumed special significance. Many researchers have been contributing techniques for tool wear measurement. An attempt has been made in this paper (i) for exploring the literature for the different tool wear monitoring techniques, (ii) advantages and limitations of the different techniques, (iii) research gaps, and to provide directions for future research. Finally, the paper concludes that much research is required in the design and development of methods using the application of machine learning and artificial intelligence for achieving accuracy, robustness, and economy in tool condition monitoring. This would help improve the reliability of the machine tool and help deliver quality products to the customer.

Keywords:
Tool wear measurement, Tool condition monitoring, Flank wear, Crater wear, Preventive maintenance, sensor-based tool monitoring.

1 Introduction

Proper knowledge of the metal removal process would help select the suitable material for the tool. Understanding the metal machining process also helps choose the right tool angles for manufacturing the quality product. The selection of the right tool angles (tool signature) would decide the quality of the manufactured product. That is, the selection of proper tool angles will determine the surface quality of the final product. The cutting tool wears out during product manufacturing, and restoring the tool angle is necessary. The device may wear out because of the continuous rubbing action of the tool with the finished surface or may be due to the agency and the chip interaction (Boothroyd 1975). Actual tool wear depends on the contact stresses, strains, and cutting temperatures during machining. Many researchers have proposed the tool wear estimation models (Koren 1978, Kramer et al. 1980, Usui et al. 1984, Kannatey-Asibu 1985). But none of these models are successful in all types of machining conditions. Friction during metal machining would also govern the power consumed during machining. Prediction of the tool wear is challenging as the machining process is a complex phenomenon. An attempt is made in the current research work for exploring the different tool wear monitoring methods proposed by other researchers.

2 Literature review

Many researchers have proposed tool wear measurement methods. The following paragraphs will discuss the working principles of different techniques with their advantages and limitations.

2.1 Tool wear measurement using sensors

Sensors are being used to capture data about the tool, process, and cutting conditions to optimize the performance during machining. Modern-day CNC machine tools are fitted with sensors and are capable of capturing real-time.

Using these sensors would drastically enhance the uptime of the machine tools and thereby the manufacturing productivity. Sensors are also helping in improving the quality of the manufactured product. Literature also reported in-process and in-cycle sensors for monitoring tool wear. The in-process sensor captures real-time data about the cutting tool. At the same time, the in-cycle sensor captures data related to the cutting tool during part change-overs. Many researchers have worked on tool wear monitoring using sensors (Shiraishi 1988, Shiraishi 1989).
It was also found that there will be a change in the surface topography as the tool wears out. Researchers have demonstrated that the extent of wear could be measured using sensors by measuring the surface topography. Few researchers have shown that the tool wear may also be measured by observing the cutting tool. Tool wear monitoring sensors should be rugged but straightforward in industrial scenarios. In the case of closed-loop systems, the tool wear sensor should collect the tool-related data in real-time. The tool wear monitoring sensors are expected to be non-contact and provide accurate and precise data in real-time. It is also likely that the sensor should not disturb the machining operation.

2.1.1. Direct tool wear measurement
The usefulness of the direct sensors will be limited to the in-cycle assessment of tool wear. Direct sensors measure the direction of the tool wear parameters accurately. Proximity sensors measure the closeness of the component from the cutting edge. The distance of the tool and the part would increase with tool wear and give the tool's exact condition (Takeyama 1967, Stoferle 1975).

In one experiment, radioactive sensors were used to assess the wear. Small amounts of a radioactive substance are deposited on the tool flank during the experiment. During the investigation, radioactive material taken out by the chip is measured. This would give the actual picture of the tool wear (Uehara 1973, Cook 1978).

Vision System
A Typical Vision system (Figure 1) comprises (with a resolution of 512x480 pixels) a frame grabber, monitor, high-end server, and advanced image processing card. In a digital image, each number represents brightness intensity. Grayscale image: '0' represents darkness and 25' represents brightness. A high-resolution camera can operate at 1000 frames/second. The internal structure of a CCD camera consists of a series of tightly packed capacitors. CCD camera has a provision for mounting different types of lenses. Literature reported using such a high-resolution camera for detecting tool wear. Frame grabber would convert an analog signal from a CCD camera into a digital image. Table 1 shows a typical digital grayscale image. The grayscale image consists of numbers between 0-255.

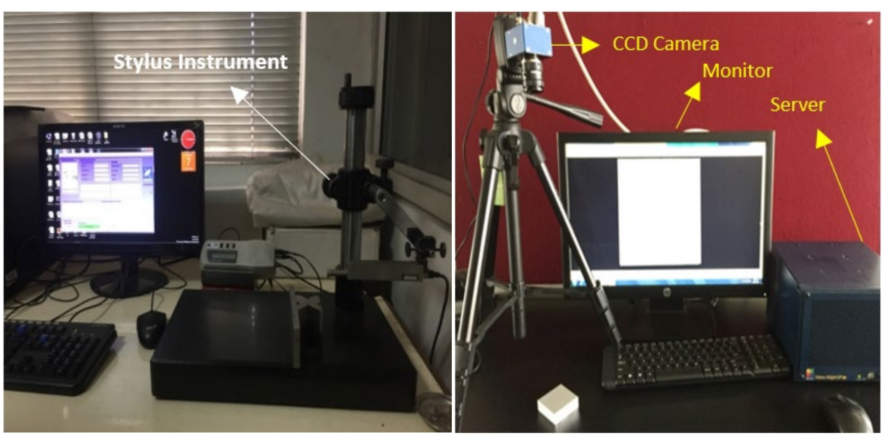

Figure 1 (a) Stylus instrument (b) Vision system and its component

The value between 0 -255 may represent different shades of gray (Table 1). Images quality can be assessed by using intensity histograms. The raw image is subjected to image pre-processing. The objective of image pre-processing is to enhance the quality of the picture. Histogram equalization is generally used for performing contrast enhancement. In contrast enhancement, each intensity value is normalized so that they are made to occupy a broader range. Filtered images can be used for studying surface textures. The image processing operation can be performed either in frequency or spatial domain. Sometimes processing of images would be simple in the frequency domain. Instead of performing

Contrast	$\sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j) \right\}, \lvert i-j\rvert = n$	(1)
Correlation	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i\ X\ j\}\ X\ P(i,j) - \{\mu_x\ X\ \mu_y\}}{\sigma_x\ X\ \sigma_y}$	(2)
Cluster Prominence	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{i+j-\mu_x-\mu_y\}^4\ X\ P(i,j)$	(3)
Dissimilarity	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j)\lvert i-j\rvert$	(4)
Energy	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{P^2(i,j)\}$	(5)
Entropy	$-\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) X log(P(i,j))$	(6)
Homogeneity	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{P(i,j)}{1+\lvert i-j\rvert}$	(7)
Maximum Probability	$max(p_{i,j})$	(8)
Sum entropy	$-\sum_{i=0}^{2G-2} P_{x+y}(i)\ log\left(P_{x+y}(i)\right)$	(9)
Difference Variance	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-\mu)^2\ P(i,j)$	(10)
Difference entropy	$-\sum_{i=0}^{G-1} P_{x+y}(i)\ log\left(P_{x+y}(i)\right)$	(11)
Inverse difference moment normalized	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j)$	(12)
Inverse difference normalized	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{P_{i,j}}{(1+\frac{\lvert i-j\rvert}{N})^2}$	(13)

Complex mathematical operations in the spatial domain can be processed quickly in the frequency domain. This will make the computations faster. The transformation from the frequency domain to the spatial domain can be done using Inverse quickly Fourier transforms. Surface texture assessment helps predict the functionality of a manufactured component. The surface texture would include roughness (small wavelength), waviness (medium wavelength), and form error (large wavelength). Texture analysis would provide essential and valuable information about the surface topography. The texture features (Equations 1-13) capture different aspects of textures. Texture parameters can be measured using a standard stylus-based instrument (Figure 1-a). Illumination forms an essential element of a vision system. Different types of illumination are possible. Researchers are using structured lighting. Illumination is a critical aspect of image processing. Variation in light intensity would drastically affect the result of measurement. Hence, all efforts should be made to control the fluctuation in light intensity. The following types of illumination are being used for tool wear assessment. The selection of light sources depends upon the type of application-Front lighting, Backlighting, and, Structured lighting.

Table 1 Digital Image

102	111	106	120	114
107	108	101	115	118
100	117	109	108	109
110	115	117	109	119
105	106	112	114	116
98	110	112	111	109
108	109	110	113	107
105	108	112	119	118

A sample co-occurrence matrix at $\theta=0^0$; $\theta=45^0$; $\theta=90^0$; $\theta=135^0$ is given in Table 2, 3, 4 and 5 respectively. These tables would capture texture information of the given image at different angles- $\theta=0^0$; $\theta=45^0$; $\theta=90^0$; $\theta=135^0$ respectively. Since the texture features are computed using these co-occurrence matrices, the mean and range of values would be used for consistency. By using these co-occurrence matrices, textural variation can be captured.

Table 2 Co-occurrence matrix at $\theta=0^0$

0	0	0	0	0
0	255	212	12	23
0	167	156	8	33
0	202	189	9	12
0	0	0	0	0

Table 3 Co-occurrence matrix at θ=45^0

0	0	0	0	0
0	254	209	14	22
0	166	146	9	32
0	199	109	10	8
0	0	0	0	0

Table 4 Co-occurrence matrix at θ=90^0

0	0	0	0	0
0	254	209	14	22
0	168	147	13	30
0	196	110	18	8
0	0	0	0	0

Table 5 Co-occurrence matrix at θ=135^0

0	0	0	0	0
0	245	189	22	12
0	186	136	6	22
0	199	109	10	8
0	0	0	0	0

A co-occurrence matrix captures spatial distribution image intensities within a texture. A co-occurrence matrix would help in computing texture features defined by Equations (1) to (13) (Haralick 1973). These 3D plots (Figure 2 a, b, and c) provide information about the texture of a tool. These plots help assess the condition of the device. For example, the height and location of the mountains can be used as parameters in classifying different textures. A worn-out tool would exhibit a unique texture. Literature reported studying the different types of devices and performing wear analysis.

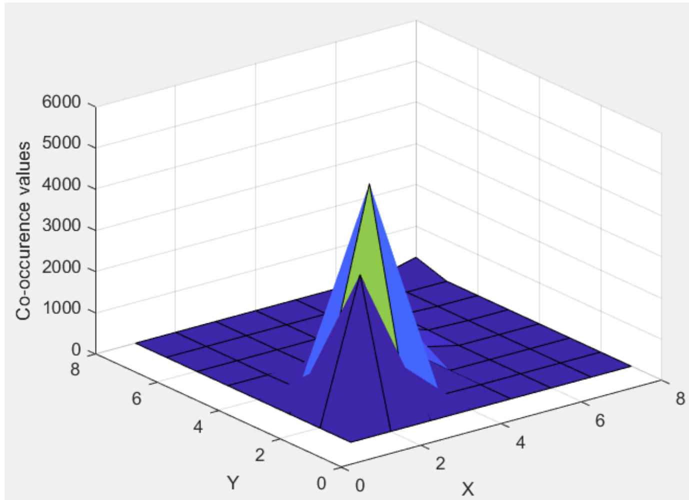

Figure 2 (a) co-occurrence matrix at θ=0^0

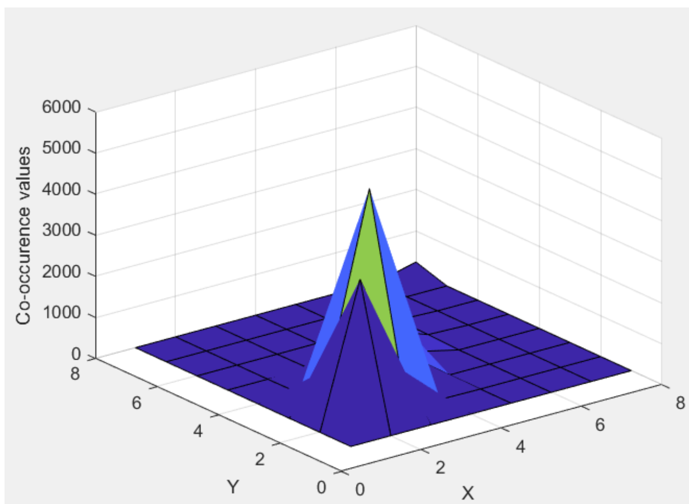

Figure 2 (b) co-occurrence matrix at θ=45^0

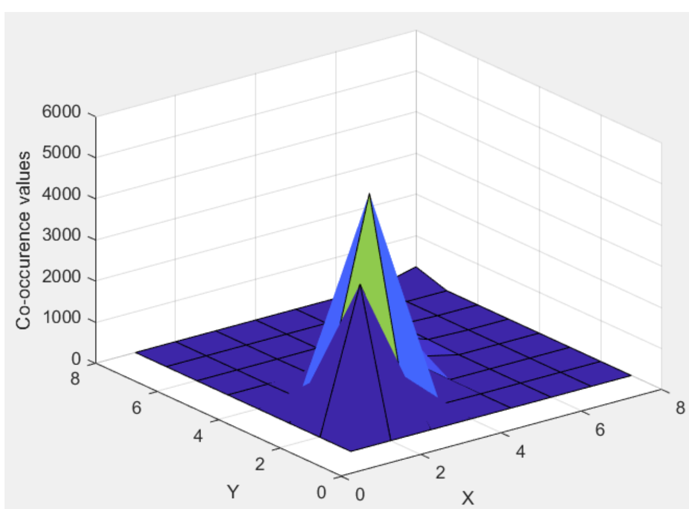

Figure 2 (c) co-occurrence matrix at θ=90^0

Literature reported all the above types of lighting for monitoring and assessing the tool wear. The kind of illumination used depends upon the problem on hand. Jeon et al. (1988) used a Vision system to study tool wear. They illuminated the flank face of the tool with laser light. They evaluated the flank wear of the device. They have not reported the accuracy and repeatability of the tool wear assessment. Lee et al. (1986) studied the tool wear (crater) using a vision system.

Several researchers use the vision system to measure the tool's wear (Soham Mehta 2019). The study showed how the wear of a turning tool could be evaluated by using a vision system. Initially, they selected a set of turning tools. They measured the tool wear using the microscope. During experimentation, the images of the turning tools were acquired using a CCD camera. Different kinds of noise may exist in the raw image. The quality of the image was enhanced by using filters. The filtered image is used for the measurement of tool wear. The study also reported good accuracy of the measured tool wear values. The repeatability of measurements was excellent.

A typically worn-out tool would exhibit three regions (Figure 3). International standards specify that VB should be less than 0.3 mm. Instead of using one sensor at a time, researchers have tried using multiple sensors for the tool wear assessment Rangwala et al. (1987). The study also reported using artificial intelligence for the tool wear assessment to overcome the disadvantages of the earlier methods. Metal machining is a complex phenomenon, and to understand machining, researchers have used Finite element methods (FEM) (Ceretti 1999, Li 2002, Klocke 2002), FDM), and AI. FEM is used for simulating the process of machining. The main advantage of the simulation is that different cutting variables such as stress, temperature strain rate, etc., that are difficult to measure through experimentation, can be easily measured by simulation (Ulutan 2009, Grzesik 2004, Balazinski 2002, Hermann 1990).

Sudden breakage of a cutting tool is known as chipping. The tool wear is gradual. The cutting tool would lose a significant amount of material in tool chipping. The device would become weak after tool breakage. This would spoil the finish of the workpiece.

2.1.2 Indirect tool wear measurement

Many of the indirect methods have parameters that correlate with the tool wear. Research work involving indirect sensors for measuring tool wear was reported. One of the researchers measured cutting forces involved in machining and then used them to assess tool wear (Konig et al. 1972). The dynamometer will measure the cutting force components along two perpendicular planes during the measurement. The problem with this technique is that it requires force signal analysis. The force signal analysis is complicated by the additional dimensions such as material properties, tool angles, build-up edge, etc. Thus accurate measurement of tool wear becomes difficult. The machining would consume more power and vibration as the tool wears out. One researcher assessed tool wear by measuring the extent of tool vibration (Takeyama et al., 1967). The rubbing of the tool flank with the workpiece results in vibration. The piezo-electric accelerometer device is attached to the tool during measurement, particularly close to the edge. It was found that the vibration signal amplitude reduces with the space of the sensor from the cutting edge increases. During measurement, the signal amplitude is compared with the reference threshold. When the amplitude is above this value, failure is predicted. During machining, the work material will be subjected to a combination of bending and fracture, resulting in the spontaneous release of energy known as acoustic emission. The study shows the extent of acoustic emission and tool wear are correlated. Thus, by measuring the acoustic emission, the researcher assessed the extent of tool wear (Domfield et al., 1980).

Kiran (2022) studied the tool wear of a face milling cutter using a Vision system. In the study, the equations (1) to (13) are used for computing the texture features. The study was conducted using a vision system connected to a CCD camera. During measurement, the image of the tool was captured, and a frame,e grabber w, was used for digitization. The image resolution was 512x480 pixels. In the digital image, each number represents image intensity. The intensity value may vary from 0 to 255. The quality of the image was assessed by using an intensity histogram. The digital image would then be filtered using suitable filters to enhance the image's quality. The image enhancement is done by using a filter. The filtered image was used to assess the wear of the cutting tool. In this work, the surface texture was used to evaluate the extent of wear. The study gives accurate results. The study also offers repeatable results. The accuracy of measurements of the method is 95.51%. Few researchers have studied machining using both coated and without coating and concluded that coated tools performed better than those without coating (Sousa et al. (, 2021).

Many researchers have studied tool wear mechanisms, using multiple sensors to overcome the individual sensor's limitations (Rangwala 1987).

3 Conclusion and direction for future research.

Many researchers have been contributing to the techniques for evaluating the dve of sensors, and researchers have proposed methods by using sensors such as proximity sensors, accelerometers, etc. The indirect measurement method of tool wear assessment is relatively cheaper than the direct method. But natural methods are more accurate in predicting tool wear. The vision method shows potential for the evaluation of tool wear. Vision technique has been successfully used for the tool wear assessment. Many researchers have studied tool wear in online and post-process means. Many researchers have used turning tools for predicting tool wear. More research is required to assess tool wear in other manufacturing processes. Much research is needed for the in-process inspection of tool wear. Improvement in tool wear measurement accuracy and repeatability require more attention by researchers. Very few researchers have used artificial neural network-based techniques to assess tool wear. Much research is needed in the area of tool wear simulation. Many of these techniques are limited to the laboratory environment. Thus, there is a requirement to design and develop robust tool wear assessment techniques, which could be deployed in the industrial environment. Much research is required in the design and development of methods using the application of machine learning and artificial intelligence for achieving accuracy, robustness, and economy in tool condition monitoring. This would help improve the reliability of the machine tool and help deliver Quality products to the customer.

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