

International Advanced Research Journal in Science, Engineering and Technology Factura '20 - National Conference On Emerging Trends In Manufacturing NSS College of Engineering, Palakkad, Kerala, India Vol. 7, Special Issue 1, August 2020



# Tool Wear Measurement of End Mill Using Machine Vision

#### Jishnoop Javaprakash<sup>1</sup>, Dr. Suresh K S<sup>2</sup>

M. Tech Student, Department of Mechanical Engineering, NSS College of Engineering, Palakkad, Kerala, India<sup>1</sup>

Professor, Department of Mechanical Engineering, NSS College of Engineering, Palakkad, Kerala, India<sup>2</sup>

Abstract: Most of the manufacturing processes require material removal in order to obtain the required shape, size, and dimensions. These processes need to have the direct contact of tool and workpiece. The quality of the work is widely affected by the tool conditions. Tool wear and vibrations will greatly affect the quality of the work, especially in the case of micro machining processes since the tool and work dimensions are comparatively small. An effective tool wear monitoring system is currently unavailable. Since automation is an integral part of industries, this paper suggests an efficient method to determine the tool wear with the help of Machine vision technology. With the help of image processing we will be able to calculate tool wear.

Keywords: Machine vision, Image processing, Tool wear, End mill.

#### I. INTRODUCTION

Machining process is always interlinked with cutting tool deuteriation and failure. A worn tool used in machining process greatly affects the machining time and product quality. The machining parameters have to be readjusted in order to use the worn tool for further machining and this will definitely reduce the surface finish of the workpiece. Many attempts have been made in order to find the tool wear using different technologies but most of them requires removal of the cutting tool from the machine which increases the production time. Different methods for monitoring and measuring tool wear developed in the past can be broadly divided into two groups: indirect methods and direct methods. Examples of indirect methods include acoustic emission monitoring, tool-tip temperature monitoring, vibration signature analysis (acceleration signals), monitoring of motor current, and cutting force monitoring. These methods normally require expensive instrumentation and are difficult to implement in a typical workshop environment. Direct methods, such as machine vision systems using a charged-couple-device (CCD) camera or optical microscope, are able to measure tool wear directly. They are simpler and require less costly equipment compared to the indirect methods. Machine learning being a rapidly developing technology and has a wide range of applications. Machine vision has been used for calculating tool wear of single point cutting tools, but in the case of end milling operations an effective method is not yet developed due to the complications of the image processing techniques to be used for calculating wear from all the cutting edges of the multi point cutter. This work is focusing on a method for combining machine vison equipped along with the machine learning technology to detect tool wear of an end milling tool.

#### **II. LITERATURE**

Many researches came up with many techniques which can be used to detect tool wear in end milling operation, but practical application of these techniques is not affordable in industries. Yiquan Dai, Kunpeng Zhu has put forward a theoretical approach in calculating tool wear in the case of micromilling using a two fluted endmill [5]. The approach has given an idea of using a machine vision setup in tool wear calculation. H. H. Shahabi & M. M. Ratnamin has made an attempt in determining surface roughness of work piece during turning operation. Their attempt mainly focused on in cycle determination of tool wear by image processing [19]. Alberto Martin and Sabri Tosunoglu deeply studied about the different image processing techniques which can be used in the field of machine vision [23]. The basic machine vision and image processing algorithms studied are grouped under five different categories. It includes grey-level segmentation or thresholding methods, edge-detection techniques, digital morphology, texture, thinning and skeletonization algorithms. D. A. Fadare and A. O. Oni in their study, developed a machine vision system based on digital image processing technique for measurement of tool wear [20]. Tool wear images were captured and ten different wear features: length, width, area, equivalent diameter, centroid, major axis length, minor axis length, solidity, eccentricity and orientation were extracted from the images. They also build a graphical user interface for easy calculation of the parameters with the help of MATLAB software.

ISO 8688 is the reference for end mill tool deterioration criteria's which suggest that when the measurable tool deterioration at any single tooth is 0.5mm then tool is worn or if the overall wear reaches 0.3mm then the tool is worn[26].



#### ISSN (Online) 2393-8021 ISSN (Print) 2394-1588

# IARJSET



International Advanced Research Journal in Science, Engineering and Technology

Factura '20 - National Conference On Emerging Trends In Manufacturing

NSS College of Engineering, Palakkad, Kerala, India

Vol. 7, Special Issue 1, August 2020



Fig.1 Wear on end mill cutter

Based on the iso standards the expected graph of the experiment is shown in the fig.2.



Fig.2 Tool deterioration values for a number of test runs plotted against cutting time

Using a blunt tool to cut material will cause my problems to the tool as well as work piece like reduced surface finish, reduced accuracy of the machine, production of large amount of heat due to rubbing action, produce noises during machining, leads to tool breakage.

#### **III. METHODOLOGY**

The experiment is conducted in different stages. First stage involves preparing the CNC machine and machine vision apparatus. The next stage is image acquisition from the machine vision before and at predetermined intervals of time. The images are then processed using different image processing techniques and tool wear is calculated. The final stage involves the development of machine learning algorithm to detect tool wear.

#### A. Experimental setup



The experiment is conducted in a vertical machining centre - LV45 equipped with automatic tool changer. The X, Y and Z strokes of 450x350x350mm having a maximum load capacity of 200kg and maximum spindle speed of 8000rpm. The setup was prepared

#### Copyright to IARJSET

#### **IARJSET**



International Advanced Research Journal in Science, Engineering and Technology

IARJSET

Factura '20 - National Conference On Emerging Trends In Manufacturing

NSS College of Engineering, Palakkad, Kerala, India

Vol. 7, Special Issue 1, August 2020



according to the fig.3. The workpiece selected is EN8 and end milling cutter of tungsten carbide material. Their properties are given in the table 1.

| MATERIAL PROPERTY     | STEEL EN8   | TUNGSTEN CARBIDE |  |  |  |  |  |  |
|-----------------------|-------------|------------------|--|--|--|--|--|--|
| Density               | 7.90g/cm3   | 15.25 g/cm3      |  |  |  |  |  |  |
| Specific heat         | 450 J/kg K  | 184 J/kg K       |  |  |  |  |  |  |
| Modulus of elasticity | 200 GPa     | 580 GPa          |  |  |  |  |  |  |
| Thermal conductivity  | 14.6W/mK    | 28 W/mK          |  |  |  |  |  |  |
| Melting range         | 1390-1440°C | 3000°C           |  |  |  |  |  |  |

#### B. Machine vision system

Machine vision is also called computer vision, is the technology which enable the machineries and computers to see objects and take decisions as humans manage tasks. There is a wide range of applications for machine vision and it can be easily programmed to user requirements. Basic machine vision system is shown in the Fig.4.The major components of machine vision system used in this experiment is Uniq vision UM-201 camera, Pc2 vision frame grabber, Lens – 50 mm, Extension tube set, LED light – Front &Back and Tripod stand.



Fig. 4 General machine vision system

The general machine vision system structure is as depicted in the fig4. The camera captures the image of the object from the required angle. Lighting system helps in illuminating the object to the required level so as to make the objects morphological structures stand out from the background. The frame grabber and processor help in receiving and analysing the image and calculating the required parameters.

#### **IV. EXPERIMENT AND IMAGE PROCESSING**

#### A. Experiment

The experimental procedure was planned accordingly so as to complete all the required objectives. The prerequisite for the experiment was programming the CNC machine for the required operations. The machine vision setup was mounted on the work bench as shown in fig.3. The tool was mounted tool holder and fixed to the automatic tool changing setup. The tool tip is cleaned using dry air every time prior to the image acquisition process. The initial image is taken and the machining operation is done for a single slot of 26cm length. The diameter of the tool is 8mm. After completing one slot, the image is taken and the process is continued until the tool is worn completely. It took about 390cm to completely wear out the end mill. And by that time 15 images of the tool were taken for inspection. The initial image and the final image is given in the fig.5.



Fig. 5 (a) initial image of the tool (b) and final image





International Advanced Research Journal in Science, Engineering and Technology Factura '20 - National Conference On Emerging Trends In Manufacturing

NSS College of Engineering, Palakkad, Kerala, India



Vol. 7, Special Issue 1, August 2020

#### B. Image processing

The image obtained from the camera will contain a lot of unwanted areas and noises as we can see in the fig 4. The difference in colour is due to change in lighting conditions of the environment. These will affect the effectiveness of the readings from the system and has to be removed using image processing. A wide varieties of image processing steps are available, of which the suitable steps are adopted for different applications. The image processing and tool wear calculation steps used in this thesis can be grouped into different stages as follows :-

- I. Pre-processing: Pre-processing involves different steps which have to be done prior to the actual processing of the image to obtain the required feasible output. It involves different steps as centering, rotating, enclosing the object in a mask and cropping.
- II. Processing: In this process different steps are done in order to make the image to clearly show the distinct differences due to the wear occurred during machining process. The different stages of processing part include grey scaling, thresholding, binarization, edge detection and finding the Region of Interest (ROI).
- III. Post processing: After the processing stage the image is ready for calculating the wear. For calculation of wear different strategies are used. The steps involved is creating a ROI, image subtraction, finding the edge points of the wear, calculating the pixel distance, converting the pixel value to the world coordinates.

#### V. RESULTS AND DISCUSSION

The results include radial wear and diametral wear of the tool. The radial wear depicts the radial length of tool which has worn out from a single tooth of the milling cutter. The diametral wear shows the value by which the actual diameter of the end mill has been worn out. The end mill used is having total 4 cutting edges. Each edge will be having different wear compared to each other depending upon the material hardness and surface irregularities. Each cutting edge has to be taken individually and calculate the wear it gives more accurate information about the wear at each edges of the tool. The obtained results of wear calculation of each individual cutting edges are given in the table II.

In practical case the diameter of the cutter is what we take into consideration, because the diameter change is what affects the machining operation. If one cutting edge is failed the other edges will compensate the cutting action but eventually the diameter keeps on decreasing during cutting action.

Diametral wear is calculated as follows

$$DW1 = RW1 + RW3$$
$$DW2 = RW2 + RW4$$

acultant diamatral waar

$$DW = \frac{DW1 + DW2}{2}$$

| Cesuitant | urametrai | wear |  |
|-----------|-----------|------|--|
|           |           |      |  |

|           |                 | TABLE II RADIA     | AL WEAI | K VALU | ES OF EA | ACH CU | TTING E                                 | DGES AND DI | AMETR                             | AL WEA | 4R                                |        |
|-----------|-----------------|--------------------|---------|--------|----------|--------|---|-------------|-----------------------------------|--------|-----------------------------------|--------|
| SL<br>NO. | NO OF<br>PASSES | MACHINED<br>LENGTH | RW 1    | RW2    | RW3      | RW4    | AVERAGE<br>4 RADIAL WEAR<br>LENGTH (RW) |             | RAGE<br>L WEAR DW1 DW2<br>TH (RW) |        | AVERAGE<br>DIAMETRAL<br>WEAR (DW) |        |
|           |                 | ( <b>mm</b> )      | Pixel   | Pixel  | Pixel    | Pixel  | Pixel                                   | mm          | Pixel                             | Pixel  | Pixel                             | mm     |
| 1         | 0               | 0                  | 0       | 0      | 0        | 0      | 0                                       | 0           | 0                                 | 0      | 0                                 | 0      |
| 2         | 1               | 260                | 2       | 2      | 2        | 2      | 2                                       | 0.03516     | 4                                 | 4      | 4                                 | 0.0703 |
| 3         | 2               | 520                | 7       | 5      | 8        | 5      | 6                                       | 0.10549     | 15                                | 10     | 12.5                              | 0.2197 |
| 4         | 3               | 780                | 14      | 8      | 11       | 9      | 10                                      | 0.17582     | 25                                | 17     | 21                                | 0.3692 |
| 5         | 4               | 1040               | 18      | 14     | 16       | 15     | 15                                      | 0.26373     | 34                                | 29     | 31.5                              | 0.5538 |
| 6         | 5               | 1300               | 24      | 21     | 24       | 19     | 22                                      | 0.3868      | 48                                | 40     | 44                                | 0.7735 |
| 7         | 7               | 1820               | 29      | 22     | 29       | 24     | 26                                      | 0.45713     | 58                                | 46     | 52                                | 0.9142 |
| 8         | 9               | 2340               | 29      | 23     | 29       | 25     | 27                                      | 0.47471     | 58                                | 48     | 53                                | 0.9318 |
| 9         | 11              | 2860               | 31      | 24     | 30       | 28     | 29                                      | 0.5098      | 61                                | 52     | 56.5                              | 0.9933 |
| 10        | 13              | 3380               | 31      | 29     | 31       | 29     | 30                                      | 0.52746     | 62                                | 58     | 60                                | 1.0548 |
| 11        | 15              | 3900               | 32      | 30     | 32       | 30     | 31                                      | 0.545       | 64                                | 60     | 62                                | 1.0900 |

### 











Fig. 6 Radial wear v/s Machined length

From fig 6, it is clearly visible that the deviation in wear of individual cutting edges are small in the initial stage till machining a length of 130 cm, after that the deviation in the radial wear is high. The main reason for this reason is that the individual cutting edges starts to deform irregularly due to rubbing action of the tool on the workpiece. The rubbing action occurs because the cutting edges has worn out and from this point the material removal will be slowed down and the surface finish reduces gradually since the tool has become blunt.



Fig. 7 Plot between Average Radial wear and machined length.

Fig 7 depicts the average values of the individual tool wear values plotted against the machined length which shows that the average radial wear is increasing upto a value of 0.38mm from machining a length of 130mm. The wear values are also under the iso standard value for tool deuteriation stated in the literature. Thus, it can be concluded that machining process is unaffected till machining a length of 130cm. The tool was used for the maximum point after that cutting action was not taking place. The maximum length the end mill can be used is 390cm. By that time the maximum radial tool wear is 0.545mm.







#### International Advanced Research Journal in Science, Engineering and Technology Factura '20 - National Conference On Emerging Trends In Manufacturing NSS College of Engineering, Palakkad, Kerala, India Vol. 7, Special Issue 1, August 2020





Fig. 8 Diametral Wear v/s Machined Length

For experimenting the difference in diameter than individual radius of end mill, plot between the diametral wear and machining length is taken as in fig 8. From which it is observed that diametral wear shows a small difference from the radial wear plot. The tool wear line shows a steady increase a little more than the radial wear plot. The wear rate increases till machining a length of 1820mm and then becomes horizontal. The calculated diametral wear at that point is 0.9mm. From the previous result it was concluded that the radial tool wear reaches till 0.38mm in radius (0.76mm diameter) and slows down, but considering the diameter the wear can reach upto 0.9mm rather than 0.76mm when considering radial wear. It is also showing that this tool is having a maximum diametral wear of 1.1mm. Which means the diameter of the end mill cutter has reduced to 6.9mm from 8mm.

For getting an idea about the material removal, the plot between the radial wear and volume of material removed is given in the fig 9.

Volume of material removed is calculated by the formula

$$volume = L \times W \times D$$

Where L is the length of each cut (26cm), W is width of cut and D is depth of cut used in machining.



Fig. 9 Tool wear v/s volume of material removed

From fig 9 it can be observed that the volume of material which can be removed effectively with precision is about 20000 mm<sup>3</sup>. The rest of the material removal is done with gradually reducing accuracy and surface finish. This is suitable in case of rough cutting operations.

#### A. Accuracy measurement

The experimentation was conducted in two stages using 3 different tools. The first stage was done by a single end mill cutter which is used for machining the workpiece in intermediate cuts of length 26mm. The tool is inspected using machine vision system after completing each slot milling. After completing the machining process, the maximum tool wear was found to be 0.545mm. Tool 3 represents this operation in the fig 10.

The second stage was conducted by using 2 end mill cutters used for machining identical operation in a continuous manner. Tool 1 and 2 represents this in the fig 10. The tools were inspected only after completing the entire length of cutting operation which was measured from the previous experiment. The total machining length is 3900mm.

#### Copyright to IARJSET

#### **IARJSET**



International Advanced Research Journal in Science, Engineering and Technology Factura '20 - National Conference On Emerging Trends In Manufacturing NSS College of Engineering, Palakkad, Kerala, India Vol. 7, Special Issue 1, August 2020





Fig. 10 Final images of Tools 1, 2 and 3 respectively.

| TABLE III MAXIMUM WEAR OF TOOLS USED |               |          |                  |             |         |  |  |  |
|--------------------------------------|---------------|----------|------------------|-------------|---------|--|--|--|
| Tool                                 | Tool Diameter |          | Value of 1 pixel | WEAR LENGTH |         |  |  |  |
| No                                   | (mm)          | (pixels) | (mm)             | (pixels)    | (mm)    |  |  |  |
| 1                                    | 8             | 478      | 0.016736         | 35          | 0.5857  |  |  |  |
| 2                                    | 8             | 410      | 0.019512         | 30          | 0.58535 |  |  |  |
| 3                                    | 8             | 455      | 0.017582         | 31          | 0.545   |  |  |  |



Fig. 11 Tool wear of 3 different tools used.

The results obtained from the test was very much similar. The calculated tool wear of both of the tools are 0.5853 and 0.5857 mm respectively. These results follow the limit determined by the ISO 8688 standard. The ISO 8688 states that when the measurable tool deuteriation reaches 0.3mm the tool is said to be worn, and the maximum deuteriation can be reached upto 0.5 mm. This shows that the machine vision system is highly accurate upto 0.0001mm. This may vary depending upon the lighting condition and focusing of the lens. This is achieved since the tools are damage free and made of good quality. The machining condition will affect the tool wear greatly.

#### VI. CONCLUTION

This experiment shows how the machine vision setup can be implemented on a vertical milling machine and a method of automatic tool wear measurement of end mill. The main success of this project is the ability to measure toolwear without interrupting the machining operation by removing the tool. This can capture images directly from the machine without tool removal. The image processing techniques was simplified form and can be directly used in the sherlock software used in the machine vision system. The reliability of the experiment was as expected and has an accuracy of 0.01mm depending upon the accuracy of image processing

#### VII. FUTURE SCOPE

The primary objective of this experiment was to establish a method to detect end mill toolwear directly from the machine without tool removal which turns to be a success. This work can be extended by performing the experiment under different machining parameters and by using different tools. Using another camera for side image capture will allow to detect flank wear of the end mill. This work is not only applicable for end mill tools but also for drilling tools by using different image processing techniques. Machining learning being an emerging trend can be implemented along with the machine vision setup for image identification process in the future.

#### Copyright to IARJSET







Factura '20 - National Conference On Emerging Trends In Manufacturing

NSS College of Engineering, Palakkad, Kerala, India

Vol. 7, Special Issue 1, August 2020

#### REFERENCES

- L. L. Alhadeff, M. B. Marshall, D. T. Curtis and T. Slatter, "Protocol for tool wear measurement in micro-milling," Wear, Vols. 420-421, no. August 2018, pp. 54-67, 2019.
- [2]. A. A. Thakre, A. V. Lad and K. Mala, "Measurements of tool wear parameters using machine vision system," Modelling and Simulation in Engineering, vol. 2019, pp. 1-10, 2019.
- [3]. G. J. Liu, Z. C. Zhou, X. Qian, W. H. Pang, G. H. Li and G. Y. Tan, "Wear Mechanism of Cemented Carbide Tool in High Speed Milling of Stainless Steel," Chinese Journal of Mechanical Engineering (English Edition), vol. 31, no. 1, 2018.
- [4]. A. Dadgari, D. Huo and D. Swailes, "Investigation on tool wear and tool life prediction in micro-milling of Ti-6Al-4V," Nami Jishu yu Jingmi Gongcheng/Nanotechnology and Precision Engineering, vol. 1, no. 4, pp. 218-225, 2018.
- [5]. Y. Dai and K. Zhu, "A machine vision system for micro-milling tool condition monitoring," Precision Engineering, vol. 52, no. May 2017, pp. 183-191, 2018.
  [6]. O. G. Moldovan, S. Dzitac, I. Moga, T. Vesselenyi and I. Dzitac, "Tool-wear analysis using image processing of the tool flank," Symmetry, vol. 9, no. 12, pp.
- [6]. O. G. Moldovan, S. Dzhač, I. Moga, I. Vesselenyi and I. Dzhač, Tool-weat analysis using image processing of the tool mank, Symmetry, vol. 9, no. 12, pp. 1-18, 2017.
  [7] A. A. Khoif and M. A. Abdullah. "Effect of Cutting Perspectors on Wear and Surface Poughness of Steipless Steel (2161) Using Milling Perspectors." Al Nahmin.
- [7]. A. A. Khleif and M. A. Abdullah, "Effect of Cutting Parameters on Wear and Surface Roughness of Stainless Steel (316L) Using Milling Process," Al-Nahrain Journal for Engineering Sciences, vol. 19, no. 2, pp. 286-292, 2017.
- [8]. R. K. R, S. N. A, V. P and S. G. S, "Analysis of Tool Wear using Machine Vision System," Iarjset, vol. 4, no. 6, pp. 7-15, 2017.
- [9]. M. S. Harish Holkar, "Optimization of End Milling Machining Parameters of AISI 321Stainless Steel using Taguchi Method," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 4, no. 4, pp. 20-23, 2016.
- [10]. M. Szydłowski, B. Powałka, M. Matuszak and P. Kochmański, "Machine vision micro-milling tool wear inspection by image reconstruction and light reflectance," Precision Engineering, vol. 44, pp. 236-244, 2016.
- [11]. J. Selmokar, "Analysis of Tool Wear in End Milling of AISI 1018 Steel," International Journal of Scientific & Engineering Research, vol. 7, no. 6, pp. 32-36, 2016.
- [12]. P. Twardowski, S. Legutko, G. M. Krolczyk and S. Hloch, "Investigation of wear and tool life of coated carbide and cubic boron nitride cutting tools in high speed milling," Advances in Mechanical Engineering, vol. 7, no. 6, pp. 1-9, 2015.
- [13]. C. Condition, E. Design and E. Work, "Flank Wear and Surface," METALURGIJA, vol. 54, no. 2, pp. 343-346, 2015.
- [14]. O. De Francisco-Ortiz, H. T. Sánchez-Reinoso and M. Estrems-Amestoy, "Development of a Robust and Accurate Positioning System in Micromachining Based on CAMERA and LCD Screen," Procedia Engineering, vol. 132, pp. 895-902, 2015.
- [15]. S. N. Oliaei and Y. Karpat, "Experimental investigations on micro milling of stavax stainless steel," Procedia CIRP, vol. 14, pp. 377-382, 2014.
- [16]. W. Li, Y. B. Guo, M. E. Barkey and J. B. Jordon, "Effect tool wear during end milling on the surface integrity and fatigue life of inconel 718," Proceedia CIRP, vol. 14, pp. 546-551, 2014.
- [17]. K. K. Chauhan and D. K. Chauhan, "Optimization of Machining Parameters of Titanium Alloy for Tool Life," Journal of Engineering, Computers & Applied Sciences (JEC&AS), vol. 2, no. 6, pp. 57-65, 2013.
- [18]. C. Zhang and J. Zhang, "On-line tool wear measurement for ball-end milling cutter based on machine vision," Computers in Industry, vol. 64, no. 6, pp. 708-719, 2013.
- [19]. H. H. Shahabi and M. M. Ratnam, "In-cycle monitoring of tool nose wear and surface roughness of turned parts using machine vision," International Journal of Advanced Manufacturing Technology, vol. 40, no. 11-12, pp. 1148-1157, 2009.
- [20]. D. A. Fadare and A. O. Oni, "Development and application of a machine vision system for measurement of tool wear," Journal of Engineering and Applied Sciences, vol. 4, no. 4, pp. 42-49, 2009.
- [21]. J. Laaksonen, "Visual Measurement and Modelling of Tool Wear in Rough Turning," 2008.
- [22]. J. H. Kim, D. K. Moon, D. W. Lee, J. S. Kim, M. C. Kang and K. H. Kim, "Tool wear measuring technique on the machine using CCD and exclusive jig," Journal of Materials Processing Technology, Vols. 130-131, pp. 668-674, 2002.
- [23]. A. Martin and S. Tosunoglu, "Image Processing Techniques For Machine Vision," Miami, Florida, pp. 1-9, 2000.
- [24]. T. Acharya and A. K. Ray, Image Processing: Principles and Applications, 2005, pp. 1-426.
- [25]. D. a. Curson, P. J. Duke, C. a. Harvey, C. Pantelis and T. R. Barnes, Machine Vision David Vernon.pdf, vol. 37, 1991, pp. 165-176.
- [26]. ISO 8688-2:1989(en) Tool life testing in milling Part 2: End milling



