International Journal on Interactive Design and Manufacturing (IJIDeM)
https://doi.org/10.1007/s12008-023-01635-8

REVIEW

Integrating intelligent machine vision techniques to advance precision manufacturing: a comprehensive survey in the context of mechatronics and beyond

Dhiren R. Patel[1] · Ankit D. Oza[2] · Manoj Kumar[3]

Received: 5 September 2023 / Accepted: 27 October 2023

Abstract

Measuring machining parameters is essential for influencing the quality and precision of the finished product in the manufacturing and machining industries. Machine vision systems, which provide an in-depth investigation of these parameters, are essential resources for this purpose. To evaluate machining parameters such as tool wear, surface roughness, and defects, this article investigates machine vision and its techniques. It also explores tool condition monitoring (TCM), a subject that is becoming more and more important. To achieve precision, high-resolution cameras with CCD or CMOS sensors in conjunction with deliberate illumination are essential. Area, compactness, and perimeter metrics are essential for assessing machining parameters because they offer insightful information about a variety of situations and enhance tool performance. By effectively utilizing these techniques, machinery can be converted into intelligent systems that improve safety, reliability, and product quality by preventing tool failure and optimizing cutting feed rates. A thorough review of the literature highlights the advantages of combining the direct and indirect TCM measurement methods, improving measurement accuracy. Additionally, the detection of tool wear problems like chipping, crater wear, and fractures is significantly aided by the integration of digital image processing techniques.

Keywords Tool condition monitoring · Machining parameters · Machine vision · Roughness parameters · Digital image processing

1 Introduction

The evaluation of machining parameters is critical for predicting tool lifespan within a machine. This makes it easier to supervise and investigate how tool wear affects both the quality of the workpiece and the economic viability of the machining and manufacturing process. Due to the rapid measurement capabilities attained through the fusion of cameras, computer hardware, and sensors, there has recently been a growing fascination with vision-based examination of tool measurements in the manufacturing sector [1–3]. The assessment of geometric attributes, dimensional precision, and surface texture, in addition to the monitoring of tool conditions (TCM), is currently regarded as a critical machining parameter within the industry. When differences in tool attributes cause specific components to fail during the design and assembly phases, optical measurements become critical. Within this context, machine vision technology has emerged as a modern instrumentation trend, owing to its user-friendliness and advanced capabilities [4]. The utilization of machine vision in manufacturing is essential in reducing production time and improving the quality of the product. These processes are commonly referred to as "automated inspection systems" [5–7].

Improving tool and instrumentation methods to include the intricate measurement of various elements such as keyways, circular components, and fractional arcs is a significant step forward. These developments include autonomous measurement methodologies that make use of localized sensors and computer hardware [8].

✉ Dhiren R. Patel
dhirenpatel85@gmail.com

Ankit D. Oza
ankitoza6060@yahoo.in

[1] Indus University, Ahmedabad, Gujarat 382115, India

[2] Department of Mechanical Engineering, Parul University, Vadodara, Gujarat 391760, India

[3] Department of Mechanical Engineering, ABES Engineering College, Ghaziabad, U.P. 201009, India

Published online: 29 November 2023

Previously, numerous researchers have delved into the utilization of machine vision to assess tools, encompassing tasks such as detecting tool wear [9, 11], monitoring tool condition [12, 13], evaluating intermittent parameters [8], appraising surface finish [14], identifying fractured inserts [15], gauging crack length [16], automating visual inspections [17], pinpointing contouring errors [18], assessing nose radius wear [19, 20], quantifying surface roughness [21], characterizing wear autonomously [5], measuring non-contact roughness [22], compensating for measurement losses in metrology [23], evaluating milling cutters [24], mitigating chatter [25, 26], confirming machine setup [27], creating models [28], and conducting dimensional measurements [29].

Tool wear can have a negative impact on the workpiece, causing damage, decreased precision in the product, compromised surface integrity, and increased chatter. Extensive research into tool wear and the evaluation of various machining parameters has highlighted the importance of machine vision-based systems and methodologies. Notably, these have proven helpful for measuring tool wear [30–32]. Figure 1 visually represents measuring tool wear using machine vision technology.

The combination of statistical methodologies and machine vision has resulted in improvements in the identification and detection of tool wear [34–39]. Many researchers in the field of machine vision have developed algorithms for segmenting tool zones and detecting edges [34, 38].

Novel methodologies for quantifying volumetric wear within the flank wear and crater regions of machinery have emerged, including "white light interferometry" [40, 41], and "stereo vision algorithms" [42]. [43] and [44] outline a thorough examination of various sensor-driven technologies, decision-making strategies, and signal processing to improve the effectiveness of machining procedures.

Numerous methodologies for monitoring tool conditions in machining tools have been proposed, including direct and indirect approaches, as well as online and offline strategies. Danes et al. [36] used statistical attributes and the "undecimated wavelet transform" to examine tool wear concerning the surface texture of the machined component during the turning operation.

Yu et al. used edge detection techniques and morphological element analysis to detect and recognize wear edges in operational scenarios [37]. Furthermore, artificial neural networks (ANN) have been used in quasi-orthogonal experiments on steel with a tungsten carbide insert to demonstrate an immediate and self-directed exploration of crater wear [38].

The assessment of tool wear within a workpiece can be accomplished using digital image processing (DIP) algorithms in MATLAB. This method employs a high-resolution CCD camera, fluorescent HF lights, and a data acquisition module [41]. Figure 2 depicts a step-by-step flowchart of the tool wear measurement process using DIP.

Schmitt et al. [11] have developed an autonomous system for detecting tool wear, which uses contour algorithms and neural networks for flank wear measurement [11, 46].

Fernandez et al. [47] developed an algorithm for the real-time detection of defects and anomalies in milling machine cutting edges, all while ensuring uninterrupted machining processes. The algorithm they proposed consists of three distinct phases: image degradation computation, the application of a smoothing filter that retains edge information, and an assessment of damage to cutting edges based on geometric attributes.

Several studies have attempted to measure and quantify the volume of the tool wear region. One such approach involves approximating the wear section as an ellipse and measuring its geometrical parameters to determine the flank wear region. In a similar vein, researchers in [19] approximated the cutting-edge section as a disk with a radius like that of the tool nose to calculate the tool nose.

Numerous tool parameters that can be evaluated using machine vision or image processing methods have been studied by researchers. The wear land area and width, perimeter, lengths of the major and minor axes, compactness, eccentricity, angle, phase orientation, solidity, equivalent diameter, extent, flank width, and nose radius are a few of these.

Digital image analysis for measuring various machining parameters, including tool condition monitoring (TCM), is the focus of this article's exploration of machine vision techniques and processes.

2 Fundamental process of machine vision system

The fundamental process of machine vision comprises five steps, and below are the details of each step [48, 49]:

2.1 Image capturing

The initial stage of the process involves capturing the image through a CCD camera as soon as the light is emitted from the source. The illuminated image is then converted into a digital format using image sensors [48, 49].

2.2 Image acquisition

To convert the optical image into a digital image, a process is followed. This process involves sub-steps such as image sensing, image data depiction, and image digitization. Ultimately, the optical image is transformed into a digital image in this step.

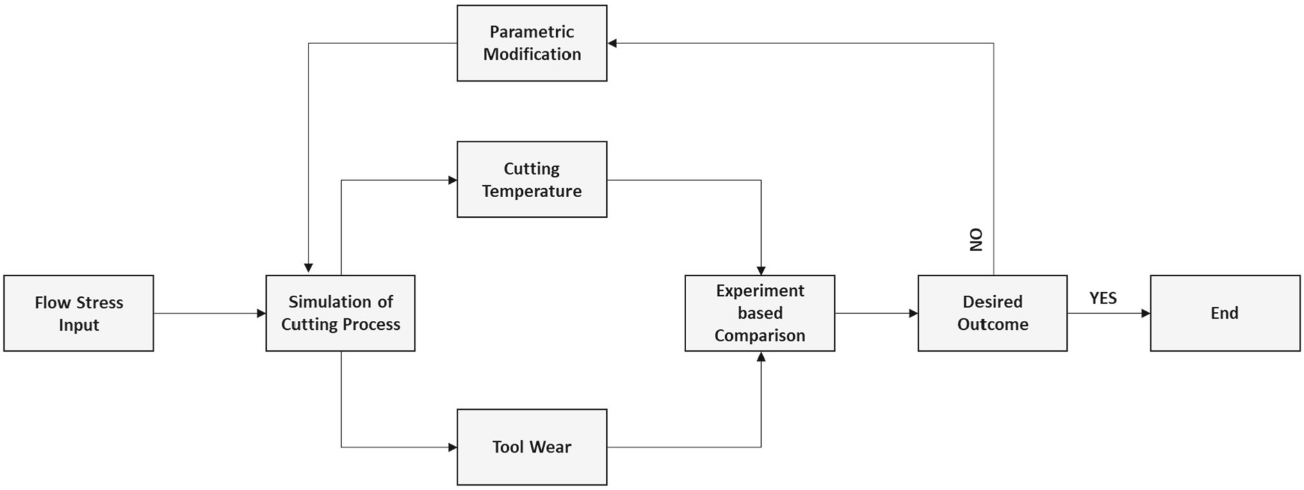
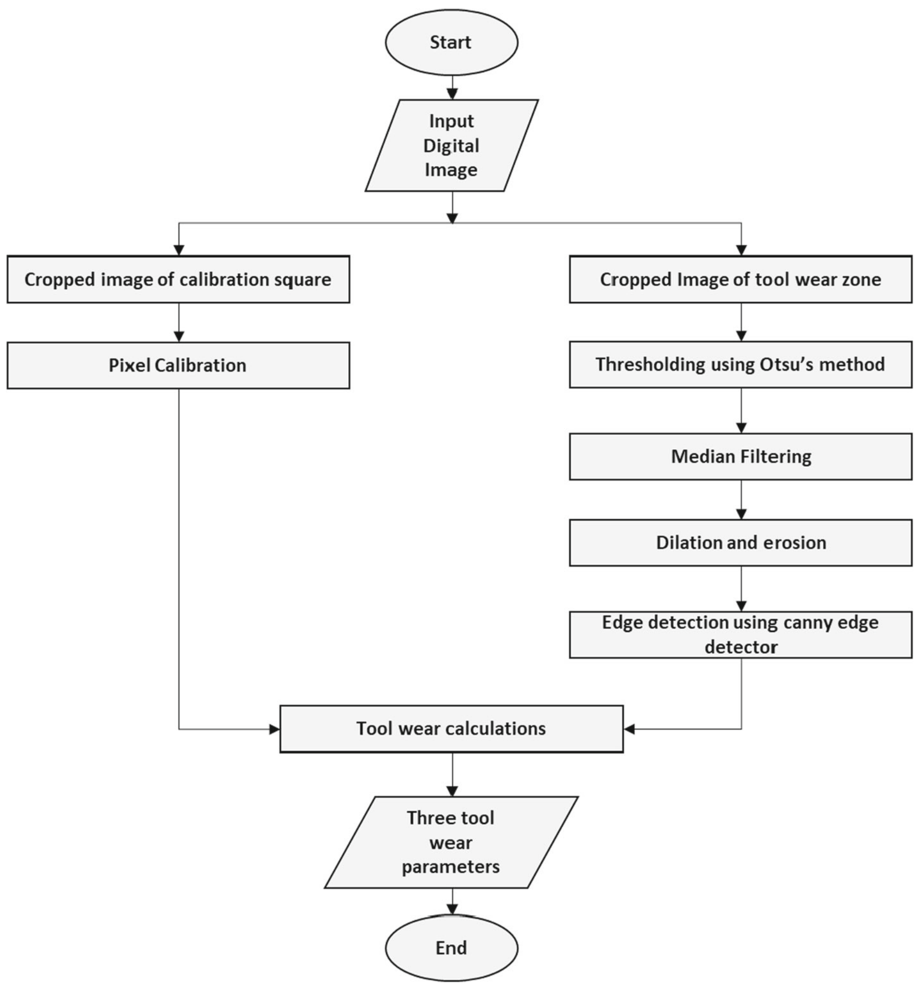


Fig. 1 Process flow diagram for calculating tool wear [33]

Fig. 2 A flowchart for measuring tool wear using the DIP algorithm [45]



2.3 Image processing

Following the start of machine vision, the next step is to arrange and prepare the pixel values inherent in an image. This process transforms the visual elements of the image into a structure appropriate for later processing steps. Geometric, neighborhood, temporal, global, and point operations are the five divisions of this phase.

2.4 Feature extraction

This step involves recognizing or identifying the inherent qualities or characteristics of the object, thing, or image.

2.5 Pattern classification

The final stage of machine vision involves pattern classification. This critical step involves identifying unfamiliar or unclassified elements and images within a well-known collection of objects and images. The fundamental procedures and methodologies involved in machine vision approaches for calculating machining parameters are shown in Fig. 3.

3 TCM measurement with machine vision

Factors such as depth of cut, workpiece material, cutting speed, feed rate, and tool material all have a significant impact on tool quality. Furthermore, coolant selection, tool geometry, and the state of the machining tool are all critical in determining both the tool's quality and the final product outcome [50, 51].

Similarly, monitoring the tool's condition and wear is crucial in determining product quality. Tool wear is typically classified into two categories, namely, crater wear and flank wear, highlighting the significance of wear measurement in machining.

A process to measure TCM is depicted in Fig. 4. The CCD camera captures images of the tooltip before and after machining. Then, these pictures are uploaded to a computer equipped with a camera interface and frame buffer. The edge detection method is used to identify and classify sharp edges to distinguish between the background and the object. The tool's tip region must then be calculated under both worn and unworn conditions. The subtraction process is carried out by aligning the images of the tooltip in both conditions with great care.

To assess tool condition monitoring (TCM), the tools are cleaned to remove chips and coolant particles, which is accomplished using air nozzles to ensure unobstructed images. Three factors must be carefully considered when capturing images for TCM measurement: the tool's positioning, its geometry or angle, and the appropriate light intensity. These elements work together to enable distinct object-background differentiation within the captured image. Visual examination of the images aids in determining the machining area or worn section of the tool. Notably, the grayscale values in this region are generally higher than in the unworn portions, making the distinction between the worn area and the unaffected zone simple. Figure 4 shows the TCM measurement process, which entails using a CCD camera to take pictures of the tool both before and after the machining operation. Then, a computer equipped with a frame buffer and camera interface components receives these images. Using an edge detection strategy, the method recognizes and classifies sharp edges to distinguish between the object and the background. The tooltip region is then computed for both the unworn and worn states, followed by a meticulous image alignment for the subtraction process involving the unworn and worn tooltip conditions [52, 53].

Chen's study [54] utilized "blob analysis" to monitor tool conditions based on grayscale pixel sets. In this method, a "blob" refers to a group of pixels. The identification of image features relies on the analysis of various characteristics. In contrast, in a separate study [5], the author focused on two types of features: pixel set area/region and perimeter, and compactness.

The region of the pixel group is determined by the number of pixels in the tool wear area. On the other hand, the perimeter of the tool wear area is defined as the entire length of a pixel. By dividing the blob area by its width, compactness is determined. Three machine vision statuses—high order, steady status area, and enhanced tool status rate—are distinguished using blob analysis. For the initial cutting edge, a high-order method is used, and the steady status area is used to lessen micro-roughness on the tool surface. The enhanced tool status rate is also used to lessen tool micro-roughness when necessary and to enhance workpiece and tool interaction. Researchers introduced these techniques, and their implementation was aided by machine vision techniques [5, 54].

The three stages presented in the machine vision system utilize techniques that yield impressive results in measuring parameters such as perimeter, area/region, and compactness. These processes demonstrate a remarkable level of accuracy in estimating wear rates, showcasing a strong correlation between the estimated and actual values.

The measurement of tool region in [6] involves the application of the RMS deviation approach with an exciting region. This technique considers several critical parameters such as the grey values present in the captured digital images, the average grey value, and the number of pixels within the desired area of focus.

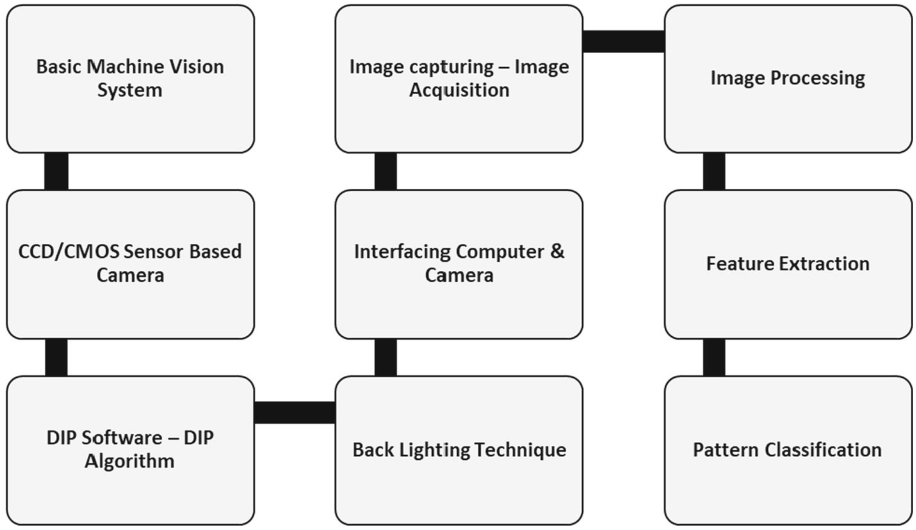


Fig. 3 Machine vision techniques' foundational procedures [14]

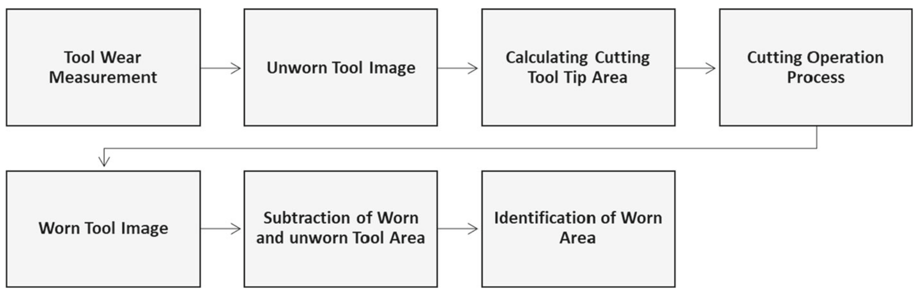


Fig. 4 Measurement of tool wear using machine vision [14]

4 Image processing techniques for measuring TCM

To measure tool wear or TCM, any machine vision approach must begin with the acquisition of images. In TCM, images of the cutting tool are taken from CCD (charged coupled device) or CMOS digital cameras, including details like the flank surface, rake face, or workpiece surface. CCD cameras use CCD sensors, which function as an array of light-sensitive elements, collecting electric charges generated by absorbed photons. These charges are transformed into electrical signals, which a frame grabber then transforms into digital images. These images are then fed into a computer for further processing [4]. CMOS sensors, on the other hand, have a faster capture rate, allowing them to capture frames at a higher frequency than CCD cameras.

However, CMOS sensors are generally less sensitive compared to CCD sensors. Continuously sensed data must be transformed into a digital format, which consists of the two crucial processes of quantization and sampling. While quantization refers to the digitization of continuous amplitude values, sampling entails the digitization of coordinate and amplitude values. To further process the image, techniques for image modification like linear interpolation, cubic convolution interpolation, and cubic interpolation can also be used [55].

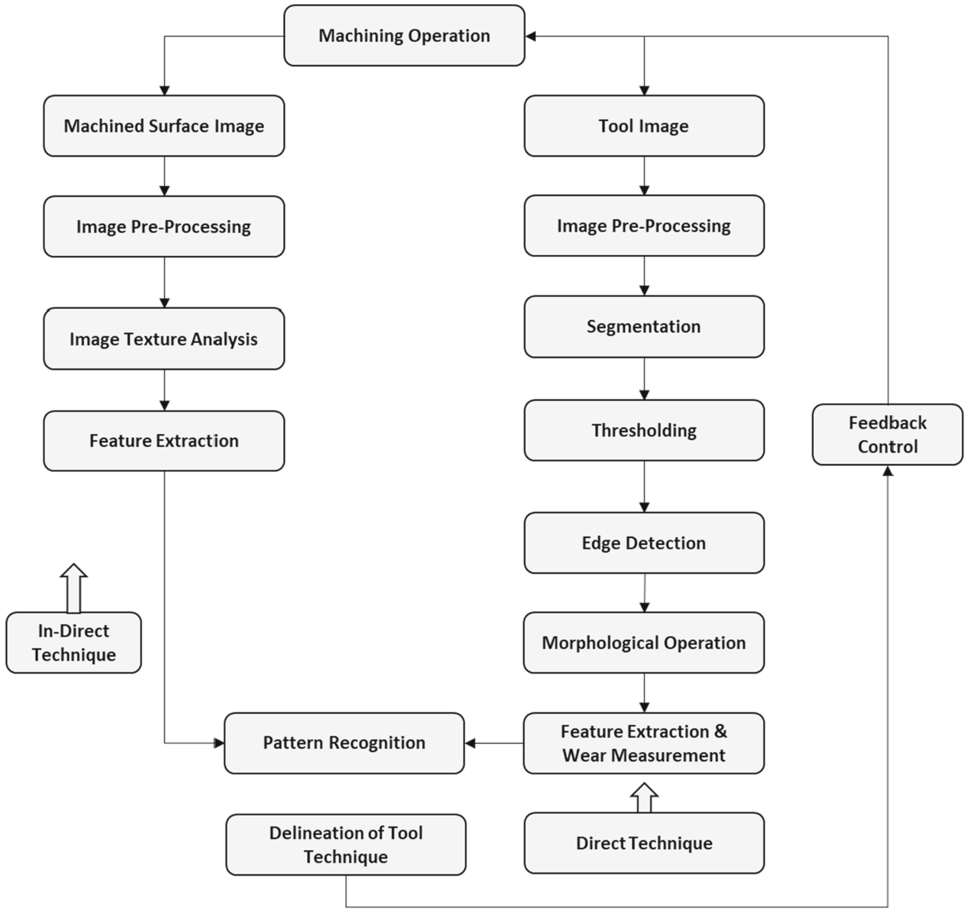
In terms of illumination, an image can be characterized by two main elements [56]:

- The total occurrence of illumination sources over the scene
- The overall illumination that the object reflects.

To enhance the quality of the images, image pre-processing techniques like histogram equalization, contrast stretching, noise reduction through filtering, and uneven illumination correction are used. Among these, histogram equalization and contrast stretching stand out as widely used and important techniques. When it comes to noise reduction, a practical approach involves the use of "low pass (LP) filtering." This method significantly enhances image smoothness by employing LP filtering in both the frequency and spatial domains [57].

Following the pre-processing phase, the next steps are edge detection and image segmentation. These steps are intended to identify the feed line edges within the image of the machined surface and to separate the post-machining region

Fig. 5 Flowchart for the DIP technique-based TCM measurement procedure



(worn area) of the cutting tool from the unworn section. Threshold and edge detection is finished before morphological operations like closing, erosion, opening, and dilation are carried out. These operations are critical for precisely identifying wear patterns. These procedures achieve a more refined morphology while preserving essential information by manipulating the grey values within the profile [58]. Figure 5 uses a flow diagram to show the measurement process for TCM using the DIP technique.

The process of measuring TCM through image processing can be categorized into two techniques: direct and indirect. The details of each technique are presented below.

4.1 Direct measurement of TCM through image processing

Crater wear and flank wear are two wear systems that occur during the useful life of cutting tools. While crater wear happens on the tool's rake face and affects the cutting process by changing the chip-tool interface, flank wear happens on the relief face of the tool as a result of rubbing action on the machined surface. Tool wear gradually increases during machining and depends on factors such as the tool material, cutting conditions, and lubricant used. Online measurement, a subset of the direct TCM measurement technique, is one of the many processes for measuring tool wear using DIP. The depth of the crater can be determined more difficultly than the flank wear by photographing the cutting tool [59].

Using machine vision technology, Peng et al. [60] introduces a novel strategy to improve tool utilization and lower costs in milling processes. The authors develop a thorough tool wear monitoring system that combines hardware and software elements to take pictures of flank wear and perform automated wear detection. In complex milling operations, the proposed wear criteria, based on VBmax, VBave, and AVB, offer a more nuanced assessment of tool wear. Experiments with nickel-based superalloy face milling are done to test the system's performance, and wear measurements from the monitoring system and an ultra-depth microscope are compared. The system's high precision is shown by the results, which have a negligible relative error of less than 7.53%. This specially created tool wear monitoring system demonstrates its effectiveness in on-machine tool wear monitoring during milling processes, indicating its potential for real-world application and significant advantages in the machining industry.

Using machine learning and computer vision techniques, [61] introduces a novel method for classifying cutting tool wear in edge profile milling processes. The authors create a new dataset with 212 tool wear images for evaluation and use B-ORCHIZ, a novel shape-based descriptor derived from wear region images. A support vector machine (SVM) is used in the study's experiments to classify the wear levels into two and three categories. Notably, B-ORCHIZ performs better than other shape descriptors, with accuracy rates ranging from 80.24% to 88.46% in a variety of situations. The research also provides a hierarchical cluster analysis, prototype wear level images, and insightful information about the development of the wear process. The findings show a potential route for automating tool wear monitoring in edge profile milling operations, highlighting the potential for improved tool wear assessment and monitoring in this particular machining domain.

The research conducted by the authors in [62] involved capturing images of tool inserts using ring light from different angles of incidence. Subsequently, the captured images were compared, and the problem of inhomogeneous illumination was addressed to obtain more accurate measurements for complex cutting edges. However, the techniques proposed in this study were not tested for other wear conditions.

The authors of [63] developed software for measuring flank wear by detecting edges from colored images. This method is based on statistical filtering, in which a group of nearby pixels is chosen, and the means and standard deviations of each primary color—red, blue, and green—are determined for each. Then, a comparison factor is obtained from these set parameters. The edge is correctly identified in the final step by considering higher comparison factor values for the cutting edge among the oxidized and worn zones. However, the resolution of this software is limited to a width of 10 mm for low flank wear.

The researcher presented a novel three-dimensional (3D) approach for quantifying tool wear in micro-milling tools with a 50 mm diameter [64]. Using a flexible camera and tool plane configuration, images with a 15 mm resolution are acquired using this technique. The captured image is then used to reconstruct a three-dimensional representation using digital focus measurement. The researchers suggested that the 3D computer-aided design (CAD) model and the 3D image of the tool could be combined to measure tool wear. Nonetheless, a comprehensive evaluation of the efficacy of this technique has yet to be completed. Numerous techniques for direct TCM measurement using DIP are listed in Table 1.

Table 1 Techniques for direct TCM measurement using DIP

Authors	Image processing technique	Machining techniques	Tool wear measurement type
Wei et al. [65]	Thresholding, median filtering	Turning, milling	Flank wear
Loizuo et al. [66]	Manual measurement with DIP software	Tool inserts	Flank wear
Lee et al. [67]	Spatial transformation	inserts	Nose wear
Prabhu et al. [68]	Shadow removal, edge detection	inserts	Flank wear
Jywe et al. [69]	Thresholding detection	Inserts	Flank wear
Garcia-Ordas et al. [70]	Contour signature	inserts	High and low wear
Joseph et al. [71]	Gaussian LPF, B-spline smoothing	Multilayer twist drill	Flank wear
Zawai et al. [72]	Edge detection	Drilling	Drill-bit

4.2 In-direct measurement of TCM through image processing

Surface finish descriptors are derived from acquired images of machined surface textures using digital image processing (DIP) methods applied to indirect TCM. TCM via image analysis employs two distinct methods: online and offline techniques. The online method entails photographing machined surfaces with CMOS or CCD cameras, which are frequently suitable for large or extended components. The offline technique, on the other hand, involves capturing surface images after specific components have been machined and is commonly used for smaller and lighter parts.

To maintain machining precision, [35] introduces a novel method for estimating the wear level of cutting inserts. The method uses statistical learning and a computer vision system to analyze 1383 flank images from a CNC parallel lathe. The use of a variety of geometrical descriptors results in the identification of three key descriptors: eccentricity, extent, and solidity, which together account for over 98% of the crucial classification information. Three wear levels—low, medium, and high—are identified by the research using a finite mixture model. Monitoring the evolution of tool wear makes it possible to estimate wear levels during machining. The results suggest a standard for tool replacement, recommending that replacement be started as soon as the wear level is about to leave the medium class, halting the progression into the high wear category. This method not only helps to maintain part tolerances but also shows improved tool life, emphasizing its usefulness in machining operations.

With the aid of ANFIS, researchers developed a method for predicting surface roughness using image texture descriptors like the arithmetic mean, standard deviation of grey levels, and spatial frequency. The investigation shows that higher surface roughness values result in a significant reduction in error rates. The discrepancy between expected and actual surface roughness measurements is less than that of the polynomial network method. It is important to note that the method has only been tested with turning operations that employ a single material for the workpiece and cutting tool. Furthermore, its application has yet to expand into the realm of continuous wear monitoring [73].

The method proposed in [74] involves an assessment and evaluation of the machined surface image's grey-level histogram to characterize its roughness. The authors have discovered a nonlinear ratio between the distribution's spread and mean values. The method, however, is sensitive to the uniformity and level of illumination of the surface because it is based on the grey-level histogram. Additionally, the grey-level histogram does not yield any information about spatial distribution.

The evaluation of surface quality using digital image analysis has been explored in [75]. According to the spacing and quantity of grey-level peaks per unit length of the scanned line in the grey-level image, the suggested method calculates surface roughness. However, the proposed one-dimensional (1D) method was found to be sensitive to noise, lighting, and lay angle, and it did not fully exploit the 2D information of the surface image.

The study described in [76] delves into the analysis of the scatter pattern produced by white light on a ground surface, intending to determine a roughness factor using vision-based methods. This factor is calculated by squaring the difference in pixel values within an 8-neighborhood. The study contrasts the roughness measurements for copper, brass, and steel made using a stylus and vision. Between 0.78 and 0.93 is the observed linear correlation coefficient. Priya et al. [77] propose that the correlation varies depending on the material, influenced by the various tearing and fracture modes encountered during grinding. To determine the technique's accuracy, a more comprehensive analysis encompassing various cutting conditions is required. Numerous techniques for in-direct TCM measurement using DIP are listed in Table 2.

In the field of machining, image processing methods for tool condition monitoring have attracted a lot of interest. Numerous studies examine direct and indirect measurement techniques, each offering particular insights. Using image texture analysis, Jurkovic st al [86] explores direct measurement with image processing for tool wear assessment. In Lutz et al.'s work, image processing and deep learning

Table 2 DIP-based in-direct TCM measurement methods Al domain light

Authors	Image processing technique	Illumination system
Gadelmawla et al. [78]	Polynomial network with self-organized adaptive learning	Two light sources were placed at an actual angle with workpiece axis
Tian et al. [79]	SD of grey level	Diffused blue light with 45 deg lnclination
Fekri-Ershad et al. [80]	Histogram analysis of 1st order statistical texture	The scatted pattern of light
[81], Baaziz et al. [82]	Spatial and freq domain-based texture examination	–
Wang et al. [83]	Threshold and flank wear analysis	–
Ong et al. [84]	Decomposition of wavelet packet	Diffused light
Ambadekar et al. [85]	GLCM approach with pixel pair spacing (PPS)	Diffused light

are used for tool condition monitoring, which is a similar strategy [87]. In terms of indirect measurement, Xiaoli Li [88] investigate using acoustic emission in combination with image processing to track tool wear. Like this, Zang et al. [89] suggest a novel technique for indirectly monitoring tool wear that includes both vibration signals and image processing. Additionally, for a thorough tool condition assessment, Machikhin et al. [90] investigate a multimodal approach combining acoustic emission and image processing. Together, these studies highlight the adaptability and potential of image processing in tool condition monitoring, addressing both the needs of direct and indirect measurement.

Manufacturers must carefully consider the economic viability of non-contact machine tool monitoring techniques. These methods have several benefits that can boost a business's bottom line, but they are also expensive. Using non-contact monitoring, tool conditions and machining operations can be evaluated in real time. This can result in less downtime and higher machine utilization, which can increase production output and reduce costs. Non-contact monitoring can reduce the production of defective parts and the need for pricey rework or scrap, leading to cost savings by identifying tool wear and other issues early on. Early recognition of tool wear and damage can help determine when to replace the tool, extending its useful life and lowering replacement costs. The need for quality control procedures and potential product recalls can be decreased by consistent monitoring, which can lead to higher-quality components and goods. Automated non-contact monitoring eliminates the need for arduous human supervision and manual inspection, potentially lowering labor costs.

5 Conclusion

Machine vision measurements of machining parameters like TCM and tool wear require a high-resolution camera with either a CCD sensor or a CMOS sensor and backlighting. Area, compactness, and perimeter play critical roles in the evaluation of machining parameters, holding significance across steady-state, higher-order conditions, and contributing to the improvement of tool status throughout the machining process. Combining the techniques with these parameters can reduce or eliminate the occurrence of tool failure. Furthermore, the machine vision process has the potential to reduce the cutting feed rate, allowing previously existing autonomous machinery to evolve into intelligent systems that improve safety, reliability, and product quality.

Following a thorough examination of the literature, the combination of direct and indirect TCM measuring techniques has the potential to improve measurement precision. This combined approach validates the results of indirect TCM measurement methods by incorporating direct methodologies within a single experimental configuration. Furthermore, the use of DIP techniques provides significant benefits in the detection of tool wear, such as autonomously identifying issues such as tool chipping, crater wear, and tool fracture. These modern techniques can effectively address these concerns, which are often difficult to discern using traditional models.

Author contributions Conceptualization: DRP; Methodology: ADO; Formal analysis and investigation: MK; Writing—original draft preparation: DRP; Writing—DRP and ADO; Supervision: DRP.

References

1. Santos, E., Xavier, W. B., Rodrigues, R. N., Botelho, S., Werhli, A.: Vision-based measurement applied to industrial instrumentation. Undefined. (2017) Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Vision-Based-Measurementapplied-to-Industrial-Santos-Xavier/3441c577f3e13d348fa8c0420bb1788da40681a3
2. Chethan, Y.D., Ravindra, H.V., Krishnegowda, Y.T.: Optimisation of machining parameters in turning Nimonic-75 using machine vision and acoustic emission signals by Taguchi technique. Measurement **144**, 144–154 (2019). https://doi.org/10.1016/j.measurement.2019.05.035
3. Penumuru, D.P., Muthuswamy, S., Karumbu, P.: Identification and classification of materials using machine vision and machine learning in the context of industry 4.0. J. Intell. Manuf. Intell. Manuf. **31**(5), 1229–1241 (2020). https://doi.org/10.1007/s10845-019-01508-6
4. Kim, J.H., Moon, D.K., Lee, D.W., Kim, J.S., Kang, M.C., Kim, K.H.: Tool wear measuring technique on the machine using CCD and exclusive jig. J. Mater. Process. Technol. **130**, 668–674 (2002). https://doi.org/10.1016/S0924-0136(02)00733-1
5. Ayub, M.A., Mohamed, A.B., Esa, A.H.: In-line inspection of roundness using machine vision. Procedia Technol. **15**, 807–816 (2014)
6. Benbarrad, T., Salhaoui, M., Kenitar, S.B., Arioua, M.: Intelligent machine vision model for defective product inspection based on machine learning. J. Sens. Actuator Netw.Netw. (2021). https://doi.org/10.3390/jsan10010007
7. Eshkevari, M., JahangoshaiRezaee, M., Zarinbal, M., Izadbakhsh, H.: Automatic dimensional defect detection for glass vials based on machine vision A heuristic segmentation method. J. Manuf. Process. **68**, 973–989 (2021). https://doi.org/10.1016/j.jmapro.2021.06.018
8. Bradley, C., Wong, Y.S.: Surface texture indicators of tool wear - a machine vision approach. Int. J. Adv. Manuf. Technol. **17**(6), 435–443 (2001). https://doi.org/10.1007/s001700170161
9. Bagga, P.J., Makhesana, M.A., Patel, K., Patel, K.M.: Tool wear monitoring in turning using image processing techniques. Mater. Today: Proc. **44**, 771–775 (2021). https://doi.org/10.1016/j.matpr.2020.10.680
10. Selvaraj, T., Balasubramani, C., Vignesh, S.H., Prabakaran, M.P.: Tool wear monitoring by image processing. Int. J. Eng. Res. **2**(8), 10 (2013)
11. Moldovan, O., Dzitac, S., Moga, I., Vesselenyi, T., Dzitac, I.: Tool-wear analysis using image processing of the tool flank. Symmetry **9**(12), 296 (2017). https://doi.org/10.3390/sym9120296
12. Chethan, Y.D., Ravindra, H., Gowda, Y.T.K., Kumar, S.B.: Machine Vision for Tool Status Monitoring in Turning Inconel 718 using Blob Analysis. Undefined (2015). Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Machine-Visionfor-Tool-Status-Monitoring-in-718-Chethan-Ravindra/4fcaaae6248444d531e06f08971bf4bb354f7e80
13. Žuvela, P., Lovrić, M., Yousefian-Jazi, A., Liu, J.J.: Ensemble learning approaches to data imbalance and competing objectives in design of an industrial machine vision system. Ind. Eng. Chem. Res. (2020). https://doi.org/10.1021/acs.iecr.9b05766
14. Patel, D.R., Kiran, M.B., Vakharia, V.: Modeling and prediction of surface roughness using multiple regressions: a noncontact approach. Eng. Rep. **2**(2), e12119 (2020). https://doi.org/10.1002/eng2.12119
15. Dhanasekar, B., Ramamoorthy, B.: Restoration of blurred images for surface roughness evaluation using machine vision. Tribol. Int.. Int. **43**(1–2), 268–276 (2010). https://doi.org/10.1016/j.triboint.2009.05.030
16. Yuan, Y., et al.: Crack length measurement using convolutional neural networks and image processing. Sensors **21**(17), 5894 (2021). https://doi.org/10.3390/s21175894
17. Patel, D.R., Vakharia, V., Kiran, M.B.: Texture classification of machined surfaces using image processing and machine learning techniques. FME Trans. **47**(4), 865–872 (2019). https://doi.org/10.5937/fmet1904865P
18. Xu, L.M., Fan, F., Hu, Y.X., Zhang, Z., Hu, D.J.: A vision-based processing methodology for profile grinding of contour surfaces. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. (2019). https://doi.org/10.1177/0954405419857401
19. Mook, W.K., Shahabi, H.H., Ratnam, M.M.: Measurement of nose radius wear in turning tools from a single 2D image using machine vision. Int. J. Adv. Manuf. Technol. **43**(3), 217–225 (2009). https://doi.org/10.1007/s00170-008-1712-1
20. Kumar, B.M., Ratnam, M.M.: Study on effect of tool nose radius wear on hybrid roughness parameters during turning using vision-based approach. IOP Conf. Ser. Mater. Sci. Eng. **530**, 012009 (2019). https://doi.org/10.1088/1757-899X/530/1/012009

21. Patel, D.R., Kiran, M.B.: Vision based prediction of surface roughness for end milling. Mater. Today Proc. **44**, 792–796 (2021). https://doi.org/10.1016/j.matpr.2020.10.709
22. Patel, D.R., Kiran, M.B.: A non-contact approach for surface roughness prediction in CNC turning using a linear regression model. Mater. Today Proc. **26**, 350–355 (2020). https://doi.org/10.1016/j.matpr.2019.12.029
23. Guardiola, B.A.: Machine vision systems: automated inspection and metrology. p. 88
24. Shuxia, G., Jiancheng, Z., Xiaofeng, J., Yin, P., Lei, W.: Mini milling cutter measurement based on machine vision. Procedia Eng. **15**, 1807–1811 (2011). https://doi.org/10.1016/j.proeng.2011.08.336
25. Szydłowski, M., Powałka, B.: Chatter detection algorithm based on machine vision. Int. J. Adv. Manuf. Technol. **62**(5–8), 517–528 (2012). https://doi.org/10.1007/s00170-011-3816-2
26. Zhou, J., Yu, J.: Chisel edge wear measurement of high-speed steel twist drills based on machine vision. Comput. Ind.. Ind. **128**, 103436 (2021). https://doi.org/10.1016/j.compind.2021.103436
27. Shahabi, H.H., Ratnam, M.M.: Assessment of flank wear and nose radius wear from workpiece roughness profile in turning operation using machine vision. Int. J. Adv. Manuf. Technol. **43**(1), 11–21 (2009). https://doi.org/10.1007/s00170-008-1688-x
28. Mahapatra, P.K., Thareja, R., Kaur, M., Kumar, A.: A machine vision system for tool positioning and its verification. Meas. Control (2015). https://doi.org/10.1177/0020294015602499
29. Li, B.: Research on geometric dimension measurement system of shaft parts based on machine vision. EURASIP J. Image Video Process (2018). https://doi.org/10.1186/s13640-018-0339-x
30. Dutta, S., Pal, S. K., Mukhopadhyay, S., Sen, R.: Application of digital image processing in tool condition monitoring: a review. Undefined, 2013, Accessed: Oct. 18 2021. [Online]. Available: https://www.semanticscholar.org/paper/Application-of-digital-imageprocessing-in-tool-A-Dutta-Pal/bd53460cef65cb12f69bfab31bc66d82d30b1e29
31. Verma, N., Vettivel, S.C., Rao, P.S., Zafar, S.: Processing, tool wear measurement using machine vision system and optimisation of machining parameters of boron carbide and rice husk ash reinforced. Mater. Res. Express **6**(8), 86 (2019). https://doi.org/10.1088/2053-1591/ab2509
32. Lins, R.G., de Araujo, P.R.M., Corazzim, M.: In-process machine vision monitoring of tool wear for cyber-physical production systems. Robot. Comput.-Integr. Manuf. **61**, 101859 (2020). https://doi.org/10.1016/j.rcim.2019.101859
33. Shao, F., Liu, Z., Wan, Y., Shi, Z.: Finite element simulation of machining of Ti-6Al-4V alloy with thermodynamical constitutive equation. Int. J. Adv. Manuf. Technol. **49**(5–8), 431–439 (2010). https://doi.org/10.1007/s00170-009-2423-y
34. Sortino, M.: Application of statistical filtering for optical detection of tool wear," undefined. Accessed: Oct. 18, 2021. [Online]. (2003) Available: https://www.semanticscholar.org/paper/Application-of-statistical-filtering-for-optical-ofSortino/cfb523844d543730b40483a7379227acf1ae110b
35. Castejón, M., Alegre, E., Barreiro, J., Hernández, L.: On-line tool wear monitoring using geometric descriptors from digital images. undefined, .Accessed: Oct. 18, 2021. [Online]. (2007). Available: https://www.semanticscholar.org/paper/On-line-tool-wear-monitoringusing-geometric-from-Castej%C3%B3n-Alegre/e4679549606817a97e11e74dcd84e1ba7850165c
36. Danesh, M., Khalili, K.: Determination of tool wear in turning process using undecimated wavelet transform and textural features. Undefined. Accessed: Oct. 18, 2021. [Online] (2015) Available: https://www.semanticscholar.org/paper/Determination-of-Tool-Wear-inTurning-Process-Using-Danesh-Khalili/e720a235f30c8d0ad8240d654627cfda6c019dfd
37. Yu, X., Lin, X., Dai, Y., Zhu, K.: Image edge detection based tool condition monitoring with morphological component analysis. Undefined (2017) Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Image-edge-detection-based-toolcondition-with-Yu-Lin/a9845773454d36ee77f4bb3cdb91c64d1a71080e
38. D'Addona, D.M., Teti, R.: Image data processing via neural networks for tool wear prediction. Procedia CIRP **12**, 252–257 (2013). https://doi.org/10.1016/j.procir.2013.09.044
39. Yu, J., Cheng, X., Lu, L., Wu, B.: A machine vision method for measurement of machining tool wear. Measurement **182**, 109683 (2021). https://doi.org/10.1016/j.measurement.2021.109683
40. Dawson, T.G., Kurfess, T.: Quantification of tool wear using white light interferometry and three-dimensional computational metrology. Undefined, 2005, Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Quantification-of-toolwear-using-white-light-and-Dawson-Kurfess/eacc9a87f117bd8a7b9c36dc50cea28cb580cf90
41. Xiong, G., Liu, J., Avila, A.: Cutting tool wear measurement by using active contour model based image processing. In: 2011 IEEE International Conference on Mechatronics and Automation, Beijing, China, pp. 670–675 (2011). https://doi.org/10.1109/ICMA.2011.5985741
42. Prasad, K. N., Ramamoorthy, B.: Tool wear evaluation by stereo vision and prediction by artificial neural network. Undefined, 2001. Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Tool-wear-evaluation-by-stereo-vision-and-byneural-Prasad-Ramamoorthy/35359076d898f2d10219cb805828be893653a4ca
43. Iliyas Ahmad, M., Yusof, Y., Daud, M.E., Latiff, K., AbdulKadir, A.Z., Saif, Y.: Machine monitoring system: a decade in review. Int. J. Adv. Manuf. Technol. **108**(11), 3645–3659 (2020). https://doi.org/10.1007/s00170-020-05620-3
44. Teti, R., Jemielniak, K., O'Donnell, G., Dornfeld, D.: Advanced monitoring of machining operations. CIRP Ann. **59**(2), 717–739 (2010)
45. Thakre, A.A., Lad, A.V., Mala, K.: Measurements of tool wear parameters using machine vision system. Model. Simul. Eng. (2019). https://doi.org/10.1155/2019/1876489
46. Wang, Y., Jia, X., Li, X., Yang, S., Zhao, H., Lee, J.: A machine vision-based monitoring system for the LCD panel cutting wheel degradation. Procedia Manuf. **48**, 49–53 (2020). https://doi.org/10.1016/j.promfg.2020.05.019
47. Fernández-Robles, L., Azzopardi, G., Alegre, E., Petkov, N.: Machine-vision-based identification of broken inserts in edge profile milling heads. Robot. Comput.-Integrated Manuf. **44**, 276–283 (2017). https://doi.org/10.1016/j.rcim.2016.10.004
48. Kurada, S., Bradley, C.: A review of machine vision sensors for tool condition monitoring. Comput. Ind.. Ind. **34**(1), 55–72 (1997). https://doi.org/10.1016/S0166-3615(96)00075-9
49. Choudhary, A. K. , AhmadKhan D.: Introduction to conditioning monitoring of mechanical systems. Soft Comput. Cond. Monit. Diagn. Electr. Mech. Syst. (2020) https://doi.org/10.1007/978-981-15-1532-3_9
50. Liu, W., Li, X., Jia, Z., Yan, H., Ma, X.: A three-dimensional triangular vision-based contouring error detection system and method for machine tools. Precis. Eng. **50**, 85–98 (2017). https://doi.org/10.1016/j.precisioneng.2017.04.016
51. Nath, C.: Integrated tool condition monitoring systems and their applications: a comprehensive review. Procedia Manuf. **48**, 852–863 (2020). https://doi.org/10.1016/j.promfg.2020.05.123
52. Zhang, C., Zhang, J.: On-line tool wear measurement for ball-end milling cutter based on machine vision. Comput. Ind.. Ind. **64**(6), 708–719 (2013). https://doi.org/10.1016/j.compind.2013.03.010
53. Ge, L., Dan, D., Li, H.: An accurate and robust monitoring method of full-bridge traffic load distribution based on YOLO-v3 machine

vision. Struct. Control. Health Monit.. Control. Health Monit. **27**(12), e2636 (2020). https://doi.org/10.1002/stc.2636
54. Chen, M.-C.: Roundness measurements for discontinuous perimeters via machine visions. Comput. Ind.. Ind. **47**(2), 185–197 (2002). https://doi.org/10.1016/S0166-3615(01)00143-9
55. Peng, R., Liu, J., Fu, X., Liu, C., Zhao, L.: Application of machine vision method in tool wear monitoring. Int. J. Adv. Manuf. Technol. **116**(3), 1357–1372 (2021). https://doi.org/10.1007/s00170-021-07522-4
56. Ambadekar, P.K., Choudhari, C.M.: CNN based tool monitoring system to predict life of cutting tool. SN Appl. Sci. **2**(5), 1–11 (2020). https://doi.org/10.1007/s42452-020-2598-2
57. Wong, S.Y., Chuah, J.H., Yap, H.J.: Technical data-driven tool condition monitoring challenges for CNC milling: a review. Int. J. Adv. Manuf. Technol. **107**(11), 4837–4857 (2020). https://doi.org/10.1007/s00170-020-05303-z
58. Hou, Q., Sun, J., Huang, P.: A novel algorithm for tool wear on-line inspection based on machine vision. Int. J. Adv. Manuf. Technol. **101**(9), 2415–2423 (2019). https://doi.org/10.1007/s00170-018-3080-9
59. Chen, W., Teng, X., Huo, D., Wang, Q.: An improved cutting force model for micro milling considering machining dynamics. Int. J. Adv. Manuf. Technol. **93**(9), 3005–3016 (2017). https://doi.org/10.1007/s00170-017-0706-2
60. Peng, R., Pang, H., Jiang, H., Hu, Y.: Study of tool wear monitoring using machine vision. Autom. Control. Comput. Sci.. Control. Comput. Sci. **54**(3), 259–270 (2020). https://doi.org/10.3103/S0146411620030062
61. García-Ordás, M.T., Alegre, E., González-Castro, V., Alaiz-Rodríguez, R.: A computer vision approach to analyze and classify tool wear level in milling processes using shape descriptors and machine learning techniques. Int. J. Adv. Manuf. Technol. **90**(5), 1947–1961 (2017). https://doi.org/10.1007/s00170-016-9541-0
62. Sun, W.-H., Yeh, S.-S.: Using the machine vision method to develop an on-machine insert condition monitoring system for computer numerical control turning machine tools. Materials (2018). https://doi.org/10.3390/ma11101977
63. Szydłowski, M., Powałka, B., Matuszak, M., Kochmański, P.: Machine vision micro-milling tool wear inspection by image reconstruction and light reflectance. Precis. Eng. **44**, 236–244 (2016). https://doi.org/10.1016/j.precisioneng.2016.01.003
64. Čerče, L., Pušavec, F., Kopač, J.: 3D cutting tool-wear monitoring in the process. J. Mech. Sci. Technol. **29**(9), 3885–3895 (2015). https://doi.org/10.1007/s12206-015-0834-2
65. Wei, W., Yin, J., Zhang, J., Zhang, H., Lu, Z.: Wear and breakage detection of integral spiral end milling cutters based on machine vision. Materials (2021). https://doi.org/10.3390/ma14195690
66. Loizou, J., Tian, W., Robertson, J., Camelio, J.: Automated wear characterization for broaching tools based on machine vision systems. J. Manuf. Syst. **37**, 558–563 (2015). https://doi.org/10.1016/j.jmsy.2015.04.005
67. Lee, W.K., Ratnam, M.M., Ahmad, Z.A.: Detection of fracture in ceramic cutting tools from workpiece profile signature using image processing and fast Fourier transform. Precis. Eng. **44**, 131–142 (2016). https://doi.org/10.1016/j.precisioneng.2015.11.001
68. Prabhu, S., Karthik Saran, S., Majumder, D., Siva Teja, P.V.: A review on applications of image processing in inspection of cutting tool surfaces. Appl. Mech. Mater. **766–767**, 635–642 (2015). https://doi.org/10.4028/www.scientific.net/AMM.766-767.635
69. Jywe, W.-Y., Hsieh, T.-H., Chen, P.-Y., Wang, M.-S., Lin, Y.-T.: Evaluation of tool scraping wear conditions by image pattern recognition system. Int. J. Adv. Manuf. Technol. **105**(1), 1791–1799 (2019). https://doi.org/10.1007/s00170-019-04360-3
70. García-Ordás, M.T., Alegre-Gutiérrez, E., González-Castro, V., Alaiz-Rodríguez, R.: Combining shape and contour features to improve tool wear monitoring in milling processes. Int. J. Prod. Res. (2018). https://doi.org/10.1080/00207543.2018.1435919
71. Kalil, J., Schueller, K., Pinto, F. de A. C., Villibor, G. P.: Monitoring of flank wear and damage on turning cutting tools by image processing. J. Eng. Exact Sci. (2020) https://doi.org/10.18540/jcecvl6iss2pp0098-0106.
72. Zawawi, M. A. M. , Teoh, S. S., Abdullah, N. B., Mohd Sazali, M. I. S. (Eds.) In: 10th International Conference on Robotics, Vision, Signal Processing and Power Applications: Enabling Research and Innovation Towards Sustainability, vol. 547. Singapore: Springer Singapore (2019). https://doi.org/10.1007/978-981-13-6447-1.
73. Ho, S.-Y., Lee, K., Chen, S.-S., Ho, S.-J.: Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system. Undefined (2002). Accessed: Oct. 19, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Accurate-modeling-and-prediction-of-surface-by-in-HoLee/7d476bb348e8a0819605ec31b46f9e2a9afce96d
74. Kapłonek, W., Nadolny, K.: Laser methods based on an analysis of scattered light for automated, in-process inspection of machined surfaces: a review. Optik **126**(20), 2764–2770 (2015). https://doi.org/10.1016/j.ijleo.2015.07.009
75. Sun, T.-H., Tien, F.-C., Tien, F.-C., Kuo, R.-J.: Automated thermal fuse inspection using machine vision and artificial neural networks. J. Intell. Manuf.Intell. Manuf. **27**(3), 639–651 (2016). https://doi.org/10.1007/s10845-014-0902-y
76. Wang, J., Qian, J., Ferraris, E., Reynaerts, D.: In-situ process monitoring and adaptive control for precision micro-EDM cavity milling. Precis. Eng. **47**, 261–275 (2017). https://doi.org/10.1016/j.precisioneng.2016.09.001
77. Priya, P., Ramamoorthy, B.: The influence of component inclination on surface finish evaluation using digital image processing. Undefined, 2007, Accessed: Oct. 19, 2021. [Online]. Available: https://www.semanticscholar.org/paper/The-influence-of-componentinclination-on-surface-Priya-Ramamoorthy/e79433a0f6e0fe63dfb01f82822f36cbdc8f93c9
78. Gadelmawla, E.S., Eladawi, A.E., Abouelatta, O.B., Elewa, I.M.: Investigation of the cutting conditions in milling operations using image texture features. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. **222**(11), 1395–1404 (2008). https://doi.org/10.1243/09544054JEM1173
79. Tian, H., Wang, D., Lin, J., Chen, Q., Liu, Z.: Surface defects detection of stamping and grinding flat parts based on machine vision. Sensors **20**(16), 4531 (2020). https://doi.org/10.3390/s20164531
80. Fekri-Ershad, S.: Texture image analysis and texture classification methods—a review. vol. 2, p. 29 (2019).
81. “Image Processing with NI Vision Development Module.” https://www.ni.com/en-lb/innovations/white-papers/06/image-processing-withni-vision-development-module.html (accessed Oct. 19, 2021).
82. Baaziz, N., Abahmane, O., Missaoui, R.: Texture feature extraction in the spatial-frequency domain for content-based image retrieval. p. 19
83. Wang, W., Wong, Y.S., Hong, G.S.: Flank wear measurement by successive image analysis. Comput. Ind.. Ind. (2005). https://doi.org/10.5555/1672858.1672934
84. Ong, P., Lee, W.K., Lau, R.J.H.: Tool condition monitoring in CNC end milling using wavelet neural network based on machine vision. Int. J. Adv. Manuf. Technol. **104**(1), 1369–1379 (2019). https://doi.org/10.1007/s00170-019-04020-6

85. Ambadekar, P.K., Choudhari, D.C.M.: Application of gray level co-occurrence matrix as a feature extraction technique to monitor wear of cutting tool. p. 9 (2018)
86. Jurkovic, J., Korosec, M., Kopac, J.: New approach in tool wear measuring technique using CCD vision system. Int. J. Mach. Tools Manuf **45**(9), 1023–1030 (2005). https://doi.org/10.1016/j.ijmachtools.2004.11.030
87. Lutz, B., Kisskalt, D., Regulin, D., Reisch, R., Schiffler, A., Franke, J.: Evaluation of deep learning for semantic image segmentation in tool condition monitoring. In: 2019 18th IEEE International Conference on Machine Learning and Applications (ICMLA), Boca Raton, FL, USA, 2019, pp. 2008–2013. https://doi.org/10.1109/ICMLA.2019.00321.
88. Li, X.: A brief review: acoustic emission method for tool wear monitoring during turning. Int. J. Mach. Tools Manuf **42**(2), 157–165 (2002). https://doi.org/10.1016/S0890-6955(01)00108-0
89. Zhang, Y., Qi, X., Wang, T., He, Y.: Tool wear condition monitoring method based on deep learning with force signals. Sensors. **23**(10), 4595 (2023). https://doi.org/10.3390/s23104595
90. Machikhin, A., Poroykov, A., Bardakov, V., Marchenkov, A., Zhgut, D., Sharikova, M., Barat, V., Meleshko, N., Kren, A.: Combined acoustic emission and digital image correlation for early detection and measurement of fatigue cracks in rails and train parts under dynamic loading. Sensors. **22**(23), 9256 (2022). https://doi.org/10.3390/s22239256