Materials Today: Proceedings 56 (2022) 1939–1946

Contents lists available at ScienceDirect

Materials Today: Proceedings

journal homepage: www.elsevier.com/locate/matpr

Machine vision for the measurement of machining parameters: A review

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ARTICLE INFO

Article history:
Available online 2 December 2021

Keywords:
Machine vision
Tool condition monitoring
DIP techniques
TCM
Machining parameters

ABSTRACT

Machining parameters have significant value in manufacturing and machining industries as they result in quality and dimensional accuracy of the product. The machining parameters are measured using various machine vision systems. In this review, machine vision and its various procedures have been discussed that are used to measure machining parameters, i.e., tool condition monitoring (TCM) tool wear and surface characteristics like surface roughness, surface defects, etc. Nowadays, Tool condition monitor is a significant machining parameter is developed in manufacturing and machining industries. The development of various techniques of machine vision explore in tool condition monitoring is of significant interest because of the improvement of non-tactile applications and computing hardware. The review also discusses the enhancement of machine vision systems in tool condition monitoring.

Selection and peer-review under responsibility of the scientific committee of the International Conference on Applied Research and Engineering 2021

1. Introduction

Measuring the machining parameters is highly significant to envisage the productive life of the tools within the machine. It is helpful in monitoring and studying the tool wear effects over the quality of the machine's workpiece and the economy of the machining and manufacturing process. Vision-based analysis from a tool measurement perspective has also gained attention in manufacturing because of its ability to measure rapidly for being integrated with the camera, computer hardware, and sensors [1–3]. These days, assessment of geometrical features, dimensional accuracy, and surface finish tool condition monitoring (TCM) concurrently is the essential machining parameters in the machining domain. Optical measurement plays a vital role if any deviation in characteristics of these tools occurs and some parts fail during the designing and assembling processes. In such a perspective, machine vision technology has become a new trend in instrumentation due to its simplicity and smartness [4]. Manufacturing based on machine vision is significant for reducing the production time and gaining a better product quality. Machine vision processes are also known as "automated inspection systems" [5–7].

The intricacy of measuring various parts like keyways, circular parts, flats having fractional arcs is a vital enhancement in tool and instrumentation techniques like autonomous measurement using localised sensors and computer hardware [8].

Previously, several researchers have considered machine vision based tool evaluation for detecting the tool wear [9–11], TCM [12,13], discontinuous parameter [8], surface finish [14], broken inserts [15], crack length [16], automated visual inspection [17], "contouring error detection" [18], "nose radius wear" [19,20], surface roughness [21], "autonomous wear characterization [5]", measurement of non-contact roughness [22], "measurement loss in metrology [23]", measurement of milling cutter [24], chatter reduction [25,26] measurement of flank wear [27], machine setup verification and modelling [28], dimensional measurement [29].

Tool wear mostly fallouts in damage to the part of a workpiece, loss of accuracy of the final item/product, reduction in surface integrity, and chatter amplification. The detailed research regarding tool wear and measurement of different machining parameters indicates that machine vision-based systems and techniques are helpful in many aspects, particularly for measuring tool wear [30–32]. Fig. 1 represents the flow chart of calculating the tool wear using machine vision technology.

When incorporated with machine vision, researchers have shown that statistical techniques also result in helpful analysis to

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https://doi.org/10.1016/j.matpr.2021.11.271
2214-7853/
Selection and peer-review under responsibility of the scientific committee of the International Conference on Applied Research and Engineering 2021

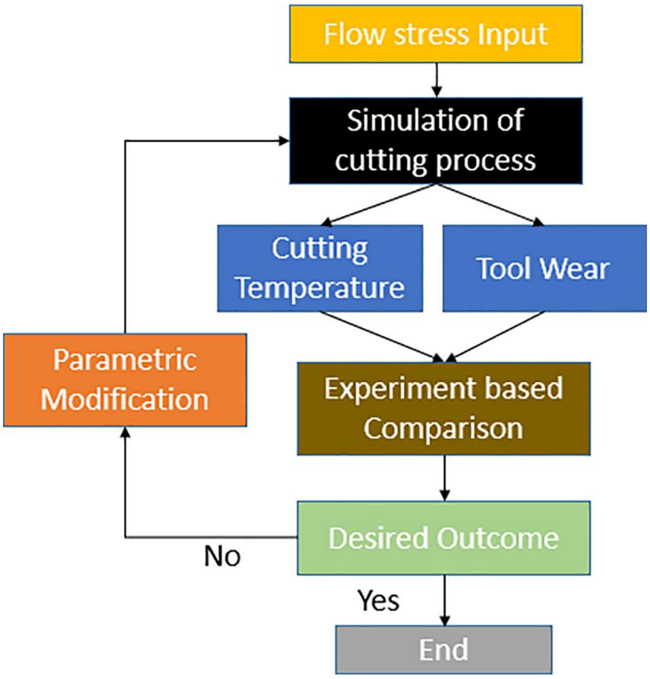

Fig. 1. Process flow chart of calculating tool wear using Finite element method [33].

identify and detect the tool wear [34–39]. Many researchers of the machine vision domain have built their algorithms regarding tool zone segmentation and edge detection [34,38].

Some of the recent techniques, such as "white light interferometry" [40,41], and "stereo vision algorithms" [42], are considered to help measure volumetric wear in flank wear and crater region of machine. A detailed analysis of different sensor-based technologies, decision-making plans, and signal processing has been presented in [43,44] for proficient machining mechanisms.

Several approaches have also been suggested for direct and indirect or on-line/offline TCM of the machining tools. In [36], Danes et al. have analysed the tool wears in view of the surface texture of the machining part throughout the turning process by using statistical features and "undecimated wavelet transform" of surface anomalies.

Yu et al. has exploited edge detection and morphological element analysis to identify and recognise the wear edges in working situations [37].

In addition to the above, Artificial Neural Network (ANN) has also been used for real-time and autonomous investigation of crater wear thru quasi-orthogonal tests on steel by exploiting tungsten carbide insert [38].

For measuring, the area of the tool wear in the workpiece, digital image processing algorithms has also been used via MATLAB. This imaging technique comprises a CCD camera (high resolution), Fluorescent HF lights, and a data acquisition module [41]. Fig. 2 represents the flow chart of the steps involved in tool wear measurement via DIP.

Another autonomous tool wear detection system was developed by Schmitt that was based on Neural networks and contour Algorithms for the measurement of flank wear [11,46].

Fernandez et al. [47] have proposed an algorithm to investigate the defect and faults in the cutting edges of milling machines inserted on-line without putting any trouble to the machining functions and operations. The proposed 3-stage algorithm comprises computation of image degrading, the smooth filter that preserves the edges, and evaluation of damage that occurs to cutting edges by exploiting geometrical properties.

Furthermore, several types of research have been conducted to quantify and measure the volume of the wear region to some approximation. Some have presented the idea of measuring the geometrical parameters for the region of flank wear by considering the wear part/section as the ellipse. In [19], the tool nose has been calculated by considering the cutting-edge section like a disk whose radius is almost equal to that of the tool nose.

The researchers have studied several tool parameters that are appropriately measured using machine vision or image processing techniques. These parameters are the wear land area and width, perimeter, major and minor axis length, compactness, eccentricity, angle and phase orientation, solidity, equivalent diameter, extent, flank width, and nose radius, etc.

This review article discusses machine vision processes and techniques, including digital image-based analysis to measure machining parameters, mainly tool condition monitoring (TCM).

2. Machine vision and its basic procedures

The basic machine vision process involves five procedures, and details of each of them are discussed as follows [48,49]:

2.1. Image capturing

The first step to initiate the process begins with image capturing via a CCD camera when the light gets emitted from the source. This image on the illuminated form is then transformed into the digital image for which image sensors are used.

2.2. Image acquisition

The optical image is transformed or changed to a digital image. There are further sub-steps under this conversion mechanism like image sensing, image data depiction, and image digitization.

2.3. Image processing

The step involves the preparation and organization of pixel values of an image. This process changes the appearance into another appropriate form to process it further. This process also comprises five sub-operators: geometric operation, neighborhood, temporal, global, and point operations.

2.4. Feature extraction

In this process, the inherent characteristics of the item, image, or object are identified.

2.5. Pattern classification

Pattern classification is the last and final processing step in machine vision. The unidentified and unknown items and images are identified from a known set of objects and images.

Fig. 3 depicts the basic procedures and operations involved in machine vision techniques for measuring machining parameters.

3. TCM measurement with machine vision

The quality of various machining tools is mainly affected by the depth of cut, the material of the workpiece, cutting speed, feed rate, and tool material. In addition to these, the machining tool's coolant used, geometry, and condition also greatly affected the quality of the tool and eventually the final product [50,51].

In the same manner, TCM and tool wear also play a significant role in decision making if the product quality is good or not. The

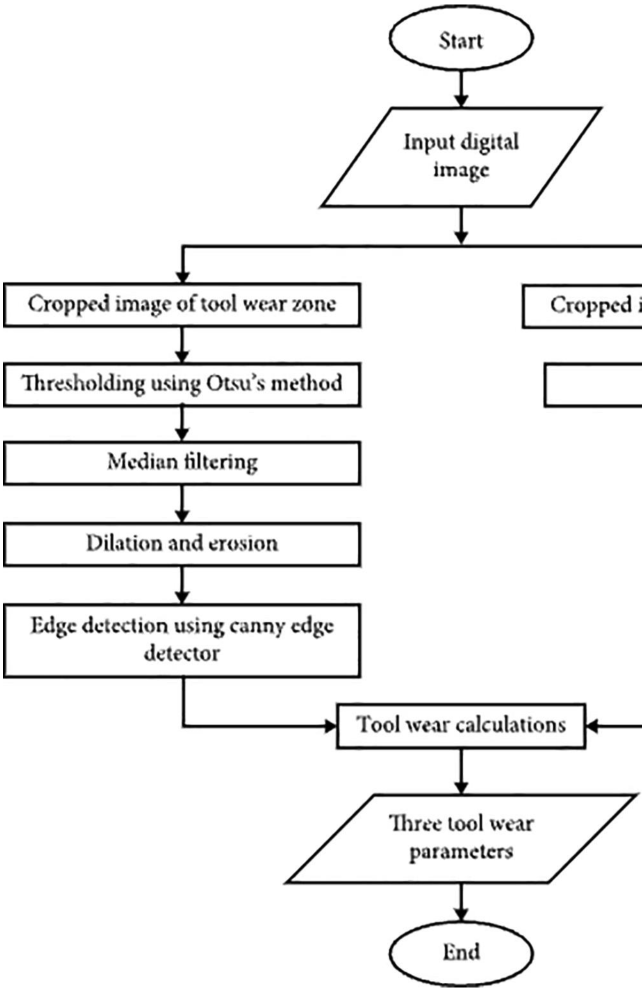

Fig. 2. Flow chart of measuring Tool wear via DIP algorithm [45].

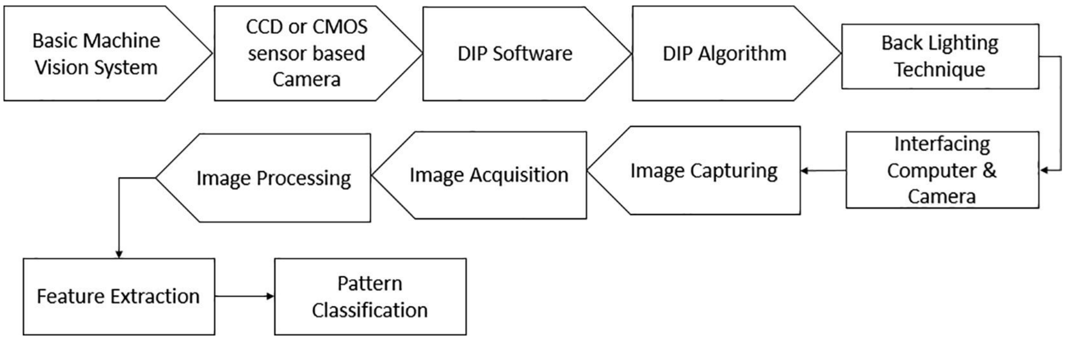

Fig. 3. Basic Processes of machine vision techniques [14].

tool wear has been categorized into two types; crater wear and flank wear. Thus, it signifies the importance of the measurement of tool wear in machining.

Fig. 4 represents the process for measuring the TCM. The tooltip images, before and after the machining processes, are taken through the CCD camera. These images are then sent to a computer having the frame buffer like the interfacing components from the camera. The edge detection approach recognizes and classifies the sharp edges to differentiate the background and object. In the next step, the tip region of the tool is calculated in both unworn and worn conditions (machining). Thus, the subtraction procedure is done with a tooltip (unworn and worn condition) by carefully handling the image alignment.

In this measurement process, all the tools are scoured from the chips and coolant particles using air nozzles to get a clear and perfect image. Three things are kept in mind while capturing the images for the Measurement of TCM.

- Tool Position
- Geometry or Angle
- Light intensity so that both object and the background of the image are identified clearly.

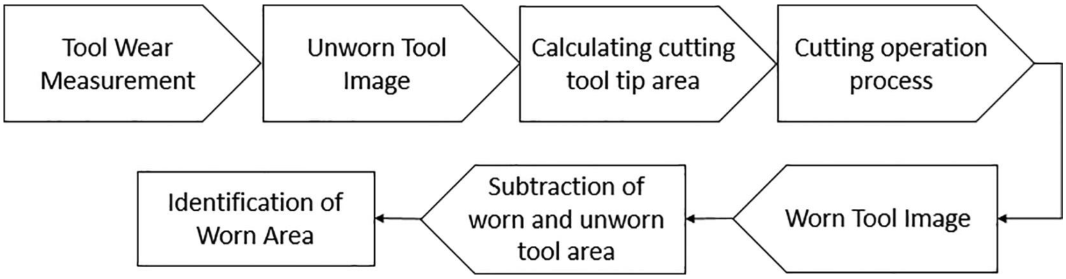

Fig. 4. Procedure of Measuring Tool wear via Machine vision [14].

The machining area (worn region of the tool) is then classified through visual inspection aid over the images. In this area, the values and level of grayscale are usually high compared to the unworn site. In this way, it becomes easy to infer the machining area (worn region) from the tool image [52,53].

Chen in [54] has used "blob analysis" to monitor the tool status from the pixel set of grayscale images. Here, the blob means "set of pixels." In this pixel analysis, several features are followed to identify image features. In [5], the author has taken into consideration two types of features in his proposed work, which are; area/region and perimeter of pixel set, and second is compactness.

Region of pixel group is measured using pixel number that is included in the tool wear area. Similarly, the perimeter can be defined as the full pixel length within the tool wear area. Whereas compactness is known as the ratio among the blob area to its width. Through this blob analysis, machine vision identifies three statuses, which are:

- High order: It is used for the fresh cutting edge.
- Steady status Area: It is used to smoothen the micro-roughness that occurs in the tool.
- Enhanced tool status rate: It is used to improve the workpiece and tool region and when there is the need to decrease the tool's micro-roughness.

The techniques of the machine vision system generate an extraordinary similarity with perimeter, area/region, and compactness in all of the presented three phases. Machine vision processes represent the excellent agreement between the estimated and actual wear rate.

In [6], the author has considered the RMS deviation approach with the exciting region for measuring the tool region. In this approach, the significant parameters are the grey values of the captured digital images, the average of all grey values, and the no. of pixels in the desired area within the focus image.

4. Image processing techniques for measuring TCM

Image acquisition is the initial step of measuring tool wear or TCM in any machine vision method. Considering TCM here, the images of the cutting tool, which can be flank surface or the rake face, or surface of the workpiece are taken with the help of a CCD ("Charged Coupled Device") camera or CMOS (Complementary metal oxide Semiconductor) digital camera. CCD cameras have CCD sensors embedded in them. CCD sensors are the photosensitive element array that gathers the electrical charges which are produced by absorbed photons. The electrical charges are transformed into electrical signals that are again transformed to digital images through a frame grabber. In the last step, the image is sent to the PC to process it [4]. CMOS is somehow different from than CCD sensor in terms of rapid capturing rate. CMOS can attain the frames more rapidly than a CCD camera.

On the contrary, CMOS sensor sensitivity is less as compared to CCD sensor. For generating a digital image, the continuous sensed data is converted into the digital form. To perform above process, two processes are considered, which are quantization and sampling. Digitization of coordinate and amplitude values is known as sampling and quantization. Linear Interpolation, cubic convolution interpolation, and cubic Interpolation are also possibly used for image modification. In addition to these, various neighbourhood processes can also be used to process the image further [55].

From an illumination perspective, image is characterized via two elements [56]:

- Total illumination source occurrence over the scene
- Complete illumination that object reflects.

Image pre-processing is done to improve the image by histogram equalization, contrast stretching, filter-based noise reduction, Compensation of inhomogeneous illumination, etc. Among these sub-techniques of pre-processing, histogram equalization and contrast stretching are the most important and commonly used processes. To minimize the noise, "low pass (LP) filtering" is considered a practical approach. It soothes the image using LP filtering in frequency and spatial domains [57].

After the pre-processing step, the edge detection and image segmentation section segment the after-machining region (worn area) of the cutting tool from that of the unworn area and identifies the feed line edges of the surface image that is already machined.

After the threshold and edge detection step, morphological procedures such as closing, erosion opening, and dilation are considered important to complete the wear processes accurately. In this procedure, a soundless morphology is attained by removing or instigating some grey values in the profile [58].

Fig. 5 shows the flow diagram of the measuring procedure of TCM using the DIP technique.

The process has been divided into two categories to measure the TCM through image processing; Direct and indirect TCM techniques details of which are as follows:

4.1. Direct measurement of TCM through image processing

There exist two wear systems for the useful life of cutting tools: crater wear and flank wear. Flank wear happens on the tool's relief face and is endorsed to the tool's rubbing action on the machined surface. On the other hand, crater wear occurs of the tool's rake face and alters the interface of the chip tool, therefore affecting the cutting process. Tool wear escalates gradually at the time of machining. It mainly relies on tool material type, cutting conditions, as well as the selected lubricant. There are so many processes of measuring the tool wear through DIP, and among them, on-line measurement is under research which is a sub-category of direct TCM measurement technique. Flank wear is easy to determine by

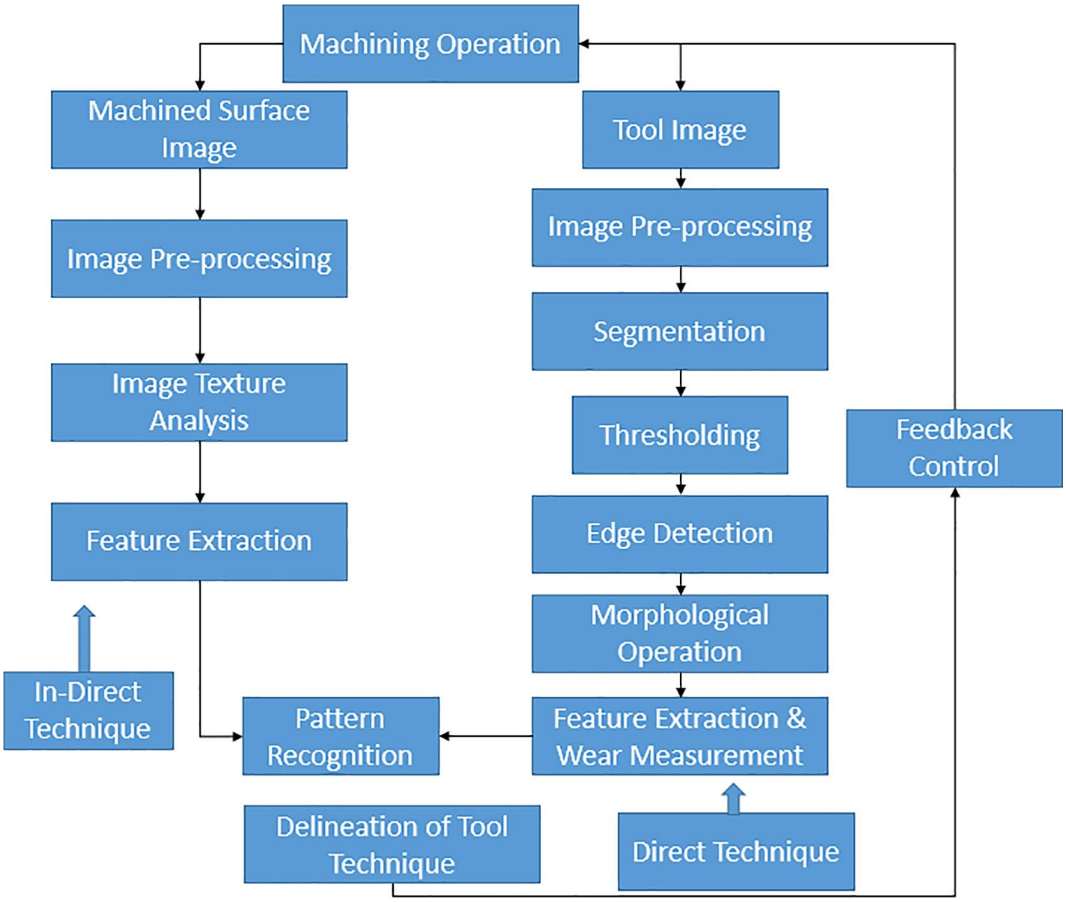

Fig. 5. Flow chart for TCM measurement procedure using DIP technique.

taking images of the cutting tool. However, an intricate and complex process is needed to find the crater's depth [59].

Pioneer work was done by Peng et al. in [60] for direct TCM measurement by taking flank wear images so tool through two fiber optic-based guided lights as well as a CCD camera. In this research, lights were attuned to illuminate the flank wear area of the tool. Authors, at first, adjusted images as two factors in vertical and horizontal track to transform the pixel to that of the length unit in microns.

In [61], the author did the work to take the image of the wear region of the tool of milling insert without uncoupling the insert through the tool holder. Here, the tool wear area was improved and differentiated from the background by fading the background via an infrared band filter while doing the image acquisition process. In addition, diode light was also synchronized using a CCD camera to take images of the tool wear region perfectly.

In [62], researchers took the tool insert image using ring light from various incidence angles. After that, a comparison was made among the captured images, and then the inhomogeneous illumination issue was minimized for more intricate cutting edges. Though, the proposed techniques by the author were not investigated for other types of wear conditions.

In [63], the software has been developed to measure the flank wear via edge detection process from colored images. The process is a statistical filtering-based technique where neighborhoods pixels were taken as a set of which mean and standard deviation (SD) were calculated for primary colors, i.e., red, blue, green. After this, a comparison factor (D) was made out of the set parameters of mean and SD. As a final step, the edge was identified precisely for higher comparison factor D values and cutting edge among the oxidized and worn zone. The proposed software of wear measurement can only be achieved for the width of low flank wear since its resolution is only 10 mm.

A 3-d technique of measuring tool wear has been proposed by [64] for the micro-milling tool with a diameter of 50 mm. The tool captures the images with a variable camera and tool plane having a resolution of 15 mm. A 3-D image of the captured image is reconstructed through digital focus measurement. At the end of the process, it has been proposed that tool wear measurement is possible if the 3D CAD model and 3-D image of the tool are combined. However, no in-depth measurement with the proposed technique has been performed (see Tables 1 and 2).

4.2. In-Direct measurement of TCM through image processing

Indirect TCM through DIP techniques can extract surface finish descriptors from the captured images of machined surface textures. Two approaches are considered for TCM from the images of machined surfaces which are on-line and offline techniques.

In the on-line technique, images are captured from machined surfaces only using CMOS or CCD cameras. On-line methods are applied on the heavy and long parts. While in the offline technique, images of the surface are captured after completing some components. In general, lightweight and small parts are measured with the help of offline techniques.

In [35], authors had presented a method to measure the roughness of the surface of the pre-turned bar (cylindrical) by making use of laser scatter pattern images that have been developed on the image of the turned surface, the time when the rotating speed of the bar was from 140 to 290 RPM. The authors have extracted

Table 1
Direct TCM measurement Techniques Using DIP.

Authors	Reference	Image processing Technique	Machining Techniques	Tool wear measurement Type
Wei et al. (2021)	[65]	Thresholding, Median Filtering	Turning, Milling	Flank wear
Loizuo et al. (2015)	[66]	Manual Measurement with DIP software	Tool inserts	Flank wear
Lee et al. (2016)	[67]	Spatial transformation	inserts	Nose wear
Prabhu et al. (2015)	[68]	Shadow removing, edge detection	inserts	Flank wear
Jywe et al. (2019)	[69]	Thresholding detection	inserts	Flank wear
Wang.j et al. (2017)	[76]	Segmentation, averaging	Generalized insert milling	Crater and flank wear
Garcia-Ordas et al. (2017)	[70]	Contour signature	inserts	High and Low wear
Joseph et al. (2020)	[71]	Gaussian LPF, B-spline smoothing	Multilayer twist drill	Flank wear
Zawai et al. (2019)	[72]	Edge Detection	Drilling	Drill-bit

Table 2
Direct TCM measurement Techniques Using DIP.

Authors	Reference	Image processing Technique	Illumination System
Gadelmawla et al. (2008)	[78]	Polynomial network with self-organized adaptive learning	Two light sources were placed at an acute angle with a workpiece axis.
Tian et al. (2020)	[79]	SD of grey level	Diffused blue light with 45 deg inclination
Fekri-Ershad et al. (2019)	[80]	Histogram analysis of 1st order statistical texture	The scattered pattern of light
Baaziz et al.	[81,82]	Spatial and freq domain-based texture examination	
Wang et al. (2005)	[83]	Threshold and flank wear analysis	–
Ong et al. (2019)	[84]	Decomposition of wavelet packet	Diffused light
Ambadekar et al. (2018)	[85]	GLCM approach with pixel pair spacing (PPS)	Diffused light

the 1st order "statistical texture descriptor" based on the grey level histogram of the captured images. During this process, surface roughness was not affected by rotation speed and ambient lighting.

In [73], the author has presented the approach to improve the surface roughness prediction using image texture descriptors such as arithmetic mean and SD of grey level, along with spatial frequency using ANFIS. From the method, it has been examined that the whole process shows less error for the high values of surface roughness. The lesser deviation was achieved among the predicted and measured roughness of the surface compared to the polynomial network approach. Nevertheless, the proposed method is applied over the turning processes with only a single combination of workpiece material and cutting tool. Furthermore, the process has not been done for progressive wear monitoring.

In [74], authors have assessed and evaluated the grey level histogram of the surface image (machined) to characterise the surface's roughness. A nonlinear ratio has been found for the spread and means the value of the distribution. As the proposed method was based on the grey level histogram, the sensitivity of uniformity and illumination degree existed. Furthermore, no data was obtained in terms of spatial distribution from the grey level histogram.

In [75], exploitation of digital image mechanism has been investigated, which is used to evaluate surface quality. The surface roughness measurement has relied on the spacing among peaks and number of the peaks of grey level per unit length of scanned line with the image of grey level. It was observed that the proposed 1D method could not fully exploit 2d information regarding surface image and was found to e sensitive to lighting, lay angle, and noise.

In [76], the author has assessed and evaluated the scatter pattern generated by the white light over the surface of the ground-based on which vision-based surface roughness factor has been derived. This roughness factor was computed using the squared difference of pixel value along with 8-neighbourhood. In research, correlation of vision-based and stylus-based roughness for copper, brass, steel has also been presented, and the linear correlation coefficient is between 0.78 and 0.93. Authors Priya et al. [77] believe that correlation keeps on changing for different materials used that mainly depend on several tearing and fracture modes for grinding of various materials. But there is a need to perform more analysis using other cutting conditions to investigate the accuracy of the technique.

5. Conclusion

To measure machining parameters like TCM and tool wear using machine vision, a high-resolution either CCD sensor or CMOS sensor-based camera is required along with the back lightening. In machining parameter measurement, there are three significant parameters as area, compactness, and perimeter, which are of great importance in the steady-state and higher-order states and for increased tool status rate all through the machining process. The failure with the tool can be minimized or removed using the techniques mentioned above and parameters. Through the machine vision process, the cutting feed rate can be reduced. Still, the previously available autonomous machines can also be developed intelligently, improving the product's safety, reliability, and quality.

From the review, it has been observed that both direct and indirect TCM measuring techniques can be used together to improve measurement performance. With such a combination, direct methods would be helpful in validating the outputs obtained using indirect TCM measurement approaches, all in a single experimental set-up. Furthermore, DIP techniques are also beneficial for easy and fast autonomous detection of tool wear such as tool chipping, crater wear, and tool fracture that otherwise become difficult to identify using other conventional models.

5.1. Future work

In future, it is suggested to put more emphasis on and do in-depth research about monitoring the degradation of the product and wear quality in terms of surface finish and dimensional integrity.

CRediT authorship contribution statement

Abdul Wahab Hashmi: Conceptualization, Data curation, Formal analysis, writing orignal draft. **Harlal Singh Mali:** Supervision, Methodology, Project administration, Resources. **Anoj Meena:** Validation, Visualization. **Irshad Ahamad Khilji:** Software, review &

editing. **Mohammad Farukh Hashmi:** Writing and investigation. **Siti Nadiah binti Mohd Safee:** Supervision,Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors would like to thank the Universiti Malaysia Pahang for providing financial support under Internal Research Grant No. RDU182202-3, as well as additional financial support under PGRS Scheme Grant No. PGRS21036 through IPS, UMP.

References

[1] E.S.F. dos Santos, W.B. Xavier, R.N. Rodrigues, S.S.C. daBotelho, A.V. Werhli, Vision Based Measurement applied to Industrial Instrumentation, IFAC-PapersOnLine 50 (2017) 788–793, https://doi.org/10.1016/j.ifacol.2017.08.509.
[2] Y.D. Chethan, H.V. Ravindra, Y.T. Krishnegowda, Optimisation of machining parameters in turning Nimonic-75 using machine vision and acoustic emission signals by Taguchi technique, Measurement 144 (2019) 144–154, https://doi.org/10.1016/j.measurement.2019.05.035.
[3] D.P. Penumuru, S. Muthuswamy, P. Karumbu, Identification and classification of materials using machine vision and machine learning in the context of industry 4.0, J. Intell. Manuf. 31 (5) (2020) 1229–1241, https://doi.org/10.1007/s10845-019-01508-6.
[4] J.-H. Kim, D.-K. Moon, D.-W. Lee, J.-S. Kim, M.-C. Kang, K.H. Kim, Tool wear measuring technique on the machine using CCD and exclusive jig, J. Mater. Process. Technol. 130-131 (2002) 668–674, https://doi.org/10.1016/S0924-0136(02)00733-1.
[5] M.A. Ayub, A. Mohamed, A.H. Esa, In-line Inspection of Roundness Using Machine Vision, undefined, 2014, Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/In-line-Inspection-of-Roundness-Using-Machine-Ayub-Mohamed/4ea863d4527309b62d3bcf3a992c1d532c123659.
[6] T. Benbarrad, M. Salhaoui, S.B. Kenitar, M. Arioua, Intelligent machine vision model for defective product inspection based on machine learning, J. Sens. Actuator Netw. 10 (1) (2021) 1, https://doi.org/10.3390/jsan10010007.
[7] M. Eshkevari, M. Jahangoshai Rezaee, M. Zarinbal, H. Izadbakhsh, Automatic dimensional defect detection for glass vials based on machine vision: a heuristic segmentation method, J. Manuf. Process. 68 (2021) 973–989, https://doi.org/10.1016/j.jmapro.2021.06.018.
[8] C. Bradley, Y.S. Wong, Surface texture indicators of tool wear - a machine vision approach, Int. J. Adv. Manuf. Technol. 17 (6) (2001) 435–443, https://doi.org/10.1007/s001700170161.
[9] Tool wear monitoring in turning using image processing techniques, Mater. Today Proc. 44 (2021) 771–775, 10.1016/j.matpr.2020.10.680.
[10] Irshad Ahamad Khilji, Sunil Pathak, S.N.B.M Safee, S Biswas, Y Singh, Nanoparticles Formation by Electrical Discharge Machining, Recent Advances in Mechanical Engineering, Springer, 1 (1) (2021) 203–210, https://doi.org/10.1007/978-981-15-7711-6_22.
[11] O. Moldovan, S. Dzitac, I. Moga, T. Vesselenyi, I. Dzitac, Tool-wear analysis using image processing of the tool flank, Symmetry 9 (12) (2017) 296, https://doi.org/10.3390/sym9120296.
[12] Y.D. Chethan, H. Ravindra, Y.T.K. Gowda, S.B. Kumar, 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-Vision-for-Tool-Status-Monitoring-in-718-Chethan-Ravindra/4fcaaae6248444d531e06f08971bf4bb354f7e80.
[13] P. Žuvela, M. Lovrić, A. Yousefian-Jazi, J.J. Liu, Ensemble learning approaches to data imbalance and competing objectives in design of an industrial machine vision system, Ind. Eng. Chem. Res. 59 (10) (2020) 4636–4645, https://doi.org/10.1021/acs.iecr.9b0576610.1021/acs.iecr.9b05766.s001.
[14] Y. Dai, K. Zhu, A machine vision system for micro-milling tool condition monitoring, undefined, 2017, Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/A-machine-vision-system-for-micro-milling-tool-Dai-Zhu/1fd7f8a538fc9db4a8da3d9a570a5d6ca22cfc3b.
[15] Restoration of blurred images for surface roughness evaluation using machine vision, Tribol. Int. 43 (1–2) (2010) 268–276, 10.1016/j.triboint.2009.05.030.
[16] Y. Yuan et al., Crack length measurement using convolutional neural networks and image processing, Sensors 21 (17) (2021) 5894, https://doi.org/10.3390/s21175894.
[17] J. Beyerer, F. Puente León, C. Frese (Eds.), Machine Vision, Springer Berlin Heidelberg, Berlin, Heidelberg, 2016.
[18] L.M. Xu, F. Fan, Y.X. Hu, Z. Zhang, D.J. Hu, 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] W.K. Mook, H.H. Shahabi, M.M. Ratnam, Measurement of nose radius wear in turning tools from a single 2D image using machine vision, Int. J. Adv. Manuf. Technol. 43 (3) (2009) 217–225, https://doi.org/10.1007/s00170-008-1712-1.
[20] B.M. Kumar, M.M. Ratnam, 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 (2019), https://doi.org/10.1088/1757-899X/530/1/012009 012009.
[21] X.W. Chen, Z.K. Zhang, Z.H. Liu, Measurement of surface roughness by computer vision in planning operations, Adv. Mater. Res. 146–147 (2011) 361–365, https://doi.org/10.4028/www.scientific.net/AMR.146-147.361.
[22] B.M. Kumar, M.M. Ratnam, Machine vision method for non-contact measurement of surface roughness of a rotating workpiece, Sens. Rev. (2015), https://doi.org/10.1108/SR-01-2014-609.
[23] B.A. Guardiola, Machine vision systems: automated inspection & metrology, p. 88.
[24] G. Shuxia, Z. Jiancheng, J. Xiaofeng, P. Yin, W. Lei, Mini milling cutter measurement based on machine vision, Procedia Eng. 15 (2011) 1807–1811, https://doi.org/10.1016/j.proeng.2011.08.336.
[25] M. Szydłowski, B. Powałka, Chatter detection algorithm based on machine vision, Int. J. Adv. Manuf. Technol. 62 (5–8) (2012) 517–528, https://doi.org/10.1007/s00170-011-3816-2.
[26] J. Zhou, J. Yu, Chisel edge wear measurement of high-speed steel twist drills based on machine vision, Comput. Ind. 128 (2021), https://doi.org/10.1016/j.compind.2021.103436 103436.
[27] H.H. Shahabi, M.M. Ratnam, 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) (2009) 11–21, https://doi.org/10.1007/s00170-008-1688-x.
[28] P.K. Mahapatra, R. Thareja, M. Kaur, A. Kumar, A machine vision system for tool positioning and its verification, Meas. Control 48 (8) (2015) 249–260, https://doi.org/10.1177/0020294015602499.
[29] B. Li, Research on geometric dimension measurement system of shaft parts based on machine vision, EURASIP J. Image Video Process. 2018 (1) (2018) 1, https://doi.org/10.1186/s13640-018-0339-x.
[30] S. Dutta, S.K. Pal, S. Mukhopadhyay, R. Sen, 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-image-processing-in-tool-A-Dutta-Pal/bd53460cef65cb12f69bfab31bc66d82d30b1e29.
[31] N. Verma, S.C. Vettivel, P.S. Rao, S. Zafar, Processing, tool wear measurement using machine vision system and optimisation of machining parameters of boron carbide and rice husk ash reinforced AA 7075 hybrid composite, Mater. Res. Express 6 (8) (2019) 0865f3, https://doi.org/10.1088/2053-1591/ab2509.
[32] R.G. Lins, P.R.M. de Araujo, M. Corazzim, In-process machine vision monitoring of tool wear for Cyber-Physical Production Systems, Robot. Comput.-Integr. Manuf. 61 (2020), https://doi.org/10.1016/j.rcim.2019.101859 101859.
[33] F. Shao, Z. Liu, Y. Wan, Z. Shi, Finite element simulation of machining of Ti-6Al-4V alloy with thermodynamical constitutive equation, Int. J. Adv. Manuf. Technol. 49 (5–8) (2010) 431–439, https://doi.org/10.1007/s00170-009-2423-y.
[34] M. Sortino, Application of statistical filtering for optical detection of tool wear, undefined, 2003, Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Application-of-statistical-filtering-for-optical-of-Sortino/cfb523844d543730b40483a7379227acf1ae110b.
[35] M. Castejón, E. Alegre, J. Barreiro, L. Hernández, On-line tool wear monitoring using geometric descriptors from digital images, undefined, 2007, Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/On-line-tool-wear-monitoring-using-geometric-from-Castej%C3%B3n-Alegre/e4679549606817a97e11e74dcd84e1ba7850165c.
[36] M. Danesh, K. Khalili, Determination of Tool Wear in Turning Process Using Undecimated Wavelet Transform and Textural Features, undefined, 2015, Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Determination-of-Tool-Wear-in-Turning-Process-Using-Danesh-Khalili/e720a235f30c8d0ad8240d654627cfda6c019dfd.
[37] X. Yu, X. Lin, Y. Dai, K. Zhu, 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-tool-condition-with-Yu-Lin/a9845773454d36ee77f4bb3cdb91c64d1a71080e.
[38] D.M. D'Addona, R. Teti, Image data processing via neural networks for tool wear prediction, Procedia CIRP 12 (2013) 252–257, https://doi.org/10.1016/j.procir.2013.09.044.
[39] J. Yu, X. Cheng, L. Lu, B. Wu, A machine vision method for measurement of machining tool wear, Measurement 182 (2021), https://doi.org/10.1016/j.measurement.2021.109683 109683.
[40] T.G. Dawson, T. Kurfess, 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-tool-wear-using-white-light-and-Dawson-Kurfess/eacc9a87f117bd8a7b9c36dc50cea28cb580cf90.
[41] G. Xiong, J. Liu, A. Avila, Cutting tool wear measurement by using active contour model based image processing, in: 2011 IEEE International Conference on Mechatronics and Automation, Beijing, China, Aug. 2011, pp. 670–675. 10.1109/ICMA.2011.5985741.
[42] K.N. Prasad, B. Ramamoorthy, 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-by-neural-Prasad-Ramamoorthy/35359076d898f2d10219cb805828be893653a4ca.
[43] M. Iliyas Ahmad, Y. Yusof, M.E. Daud, K. Latiff, A.Z. Abdul Kadir, Y. Saif, Machine monitoring system: a decade in review, Int. J. Adv. Manuf. Technol. 108 (11) (2020) 3645–3659, https://doi.org/10.1007/s00170-020-05620-3.
[44] R. Teti, K. Jemielniak, G. O'Donnell, D. Dornfeld, Advanced monitoring of machining operations, undefined, 2010, Accessed: Oct. 18, 2021. [Online]. Available: https://www.semanticscholar.org/paper/Advanced-monitoring-of-machining-operations-Teti-Jemielniak/612c50248d87ae395a06a77d4792ab447d932545.
[45] A.A. Thakre, A.V. Lad, K. Mala, Measurements of tool wear parameters using machine vision system, Model. Simul. Eng. 2019 (2019), https://doi.org/10.1155/2019/1876489.
[46] A Machine Vision Based Monitoring System for the LCD Panel Cutting Wheel Degradation, Procedia Manuf. 48 (2020) 49–53, 10.1016/j.promfg.2020.05.019.
[47] Machine-vision-based identification of broken inserts in edge profile milling heads, Robot. Comput.-Integr. Manuf. 44 (2017) 276–283, 10.1016/j.rcim.2016.10.004.
[48] S. Kurada, C. Bradley, A review of machine vision sensors for tool condition monitoring, Comput. Ind. 34 (1) (1997) 55–72, https://doi.org/10.1016/S0166-3615(96)00075-9.
[49] A.K. Choudhary, D. Ahmad Khan, Introduction to conditioning monitoring of mechanical systems, Soft Comput. Cond. Monit. Diagn. Electr. Mech. Syst. (2020) 205–230, https://doi.org/10.1007/978-981-15-1532-3_9.
[50] W. Liu, X. Li, Z. Jia, H. Yan, X. Ma, A three-dimensional triangular vision-based contouring error detection system and method for machine tools, Precis. Eng. 50 (2017) 85–98, https://doi.org/10.1016/j.precisioneng.2017.04.016.
[51] C. Nath, Integrated tool condition monitoring systems and their applications: a comprehensive review, Procedia Manuf. 48 (2020) 852–863, https://doi.org/10.1016/j.promfg.2020.05.123.
[52] C. Zhang, J. Zhang, On-line tool wear measurement for ball-end milling cutter based on machine vision, Comput. Ind. 64 (6) (2013) 708–719, https://doi.org/10.1016/j.compind.2013.03.010.
[53] L. Ge, D. Dan, H. Li, An accurate and robust monitoring method of full-bridge traffic load distribution based on YOLO-v3 machine vision, Struct. Control Health Monit. 27 (12) (2020), https://doi.org/10.1002/stc.2636 e2636.
[54] M.-C. Chen, Roundness measurements for discontinuous perimeters via machine visions, Comput. Ind. 47 (2) (2002) 185–197, https://doi.org/10.1016/S0166-3615(01)00143-9.
[55] R. Peng, J. Liu, X. Fu, C. Liu, L. Zhao, Application of machine vision method in tool wear monitoring, Int. J. Adv. Manuf. Technol. 116 (3) (2021) 1357–1372, https://doi.org/10.1007/s00170-021-07522-4.
[56] P.K. Ambadekar, C.M. Choudhari, CNN based tool monitoring system to predict life of cutting tool, SN Appl. Sci. 2 (5) (2020) 1–11, https://doi.org/10.1007/s42452-020-2598-2.
[57] S.Y. Wong, J.H. Chuah, H.J. Yap, Technical data-driven tool condition monitoring challenges for CNC milling: a review, Int. J. Adv. Manuf. Technol. 107 (11) (2020) 4837–4857, https://doi.org/10.1007/s00170-020-05303-z.
[58] Q. Hou, J. Sun, P. Huang, A novel algorithm for tool wear on-line inspection based on machine vision, Int. J. Adv. Manuf. Technol. 101 (9) (2019) 2415–2423, https://doi.org/10.1007/s00170-018-3080-9.
[59] W. Chen, X. Teng, D. Huo, Q. Wang, An improved cutting force model for micro milling considering machining dynamics, Int. J. Adv. Manuf. Technol. 93 (9) (2017) 3005–3016, https://doi.org/10.1007/s00170-017-0706-2.
[60] R. Peng, H. Pang, H. Jiang, Y. Hu, Study of tool wear monitoring using machine vision, Autom. Control Comput. Sci. 54 (3) (2020) 259–270, https://doi.org/10.3103/S0146411620030062.
[61] M.T. García-Ordás, E. Alegre, V. González-Castro, R. Alaiz-Rodríguez, 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) (2017) 1947–1961, https://doi.org/10.1007/s00170-016-9541-0.
[62] W.-H. Sun, S.-S. Yeh, Using the machine vision method to develop an on-machine insert condition monitoring system for computer numerical control turning machine tools, Materials 11 (10) (2018) 10, https://doi.org/10.3390/ma11101977.
[63] Machine vision micro-milling tool wear inspection by image reconstruction and light reflectance, Precis. Eng. 44 (2016) 236–244, 10.1016/j.precisioneng.2016.01.003.
[64] L. Čerče, F. Pušavec, J. Kopač, 3D cutting tool-wear monitoring in the process, J. Mech. Sci. Technol. 29 (9) (2015) 3885–3895, https://doi.org/10.1007/s12206-015-0834-2.
[65] W. Wei, J. Yin, J. Zhang, H. Zhang, Z. Lu, Wear and breakage detection of integral spiral end milling cutters based on machine vision", Materials 14 (19) (2021) 19, https://doi.org/10.3390/ma14195690.
[66] Automated wear characterisation for broaching tools based on machine vision systems, J. Manuf. Syst. 37 (2015) 558–563, 10.1016/j.jmsy.2015.04.005.
[67] Detection of fracture in ceramic cutting tools from workpiece profile signature using image processing and fast Fourier transform, Precis. Eng. 44 (2016) 131–142, 10.1016/j.precisioneng.2015.11.001.
[68] S. Prabhu, S. Karthik Saran, D. Majumder, P.V. Siva Teja, A review on applications of image processing in inspection of cutting tool surfaces, Appl. Mech. Mater. 766–767 (2015) 635–642, https://doi.org/10.4028/www.scientific.net/AMM.766-767.635.
[69] W.-Y. Jywe, T.-H. Hsieh, P.-Y. Chen, M.-S. Wang, Y.-T. Lin, Evaluation of tool scraping wear conditions by image pattern recognition system, Int. J. Adv. Manuf. Technol. 105 (1) (2019) 1791–1799, https://doi.org/10.1007/s00170-019-04360-3.
[70] M.T. García-Ordás, E. Alegre-Gutiérrez, V. González-Castro, R. Alaiz-Rodríguez, Combining shape and contour features to improve tool wear monitoring in milling processes, Int. J. Prod. Res. (2018), Accessed: Oct. 19, 2021. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/00207543.2018.1435919.
[71] J.K.K. Junior, J.K. Schueller, F. de A.C. Pinto, G.P. Villibor, Monitoring of flank wear and damage on turning cutting tools by image processing, J. Eng. Exact Sci. 6 (2) (2020) 2. 10.18540/jcecvl6iss2pp0098-0106.
[72] M.A.M. Zawawi, S.S. Teoh, N.B. Abdullah, M.I.S. Mohd Sazali, (Eds.), 10th International Conference on Robotics, Vision, Signal Processing and Power Applications: Enabling Research and Innovation Towards Sustainability, vol. 547. Springer Singapore, Singapore, 2019. 10.1007/978-981-13-6447-1.
[73] S.-Y. Ho, K. Lee, S.-S. Chen, S.-J. Ho, 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-Ho-Lee/7d476bb348e8a0819605ec31b46f9e2a9afce96d.
[74] Laser methods based on an analysis of scattered light for automated, in-process inspection of machined surfaces: A review, Optik 126 (20) (2015) 2764–2770, 10.1016/j.ijleo.2015.07.009.
[75] T.-H. Sun, F.-C. Tien, F.-C. Tien, R.-J. Kuo, Automated thermal fuse inspection using machine vision and artificial neural networks, J. Intell. Manuf. 27 (3) (2016) 639–651, https://doi.org/10.1007/s10845-014-0902-y.
[76] Wang.j, j. Qian, E. Ferriaris, D. Reynaaerts, In-situ process monitoring and adaptive control for precision micro-EDM cavity milling, Precis. Eng. 47 (2017) 261–275, https://doi.org/10.1016/j.precisioneng.2016.09.001.
[77] P. Priya, B. Ramamoorthy, 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-component-inclination-on-surface-Priya-Ramamoorthy/e79433a0f6e0fe63dfb01f82822f36cbdc8f93c9
[78] E.S. Gadelmawla, A.E. Eladawi, O.B. Abouelatta, I.M. Elewa, Investigation of the cutting conditions in milling operations using image texture features, Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. 222 (11) (2008) 1395–1404, https://doi.org/10.1243/09544054JEM1173.
[79] H. Tian, D. Wang, J. Lin, Q. Chen, Z. Liu, Surface defects detection of stamping and grinding flat parts based on machine vision, Sensors 20 (16) (2020) 4531, https://doi.org/10.3390/s20164531.
[80] S. Fekri-Ershad, Texture image analysis and texture classification methods - a review 2 (2019) 29.
[81] Image Processing with NI Vision Development Module, https://www.ni.com/en-lb/innovations/white-papers/06/image-processing-with-ni-vision-development-module.html (accessed Oct. 19, 2021).
[82] N. Baaziz, O. Abahmane, R. Missaoui, Texture feature extraction in the spatial-frequency domain for content-based image retrieval, p. 19.
[83] W. Wang, W. S, H. S, Flank wear measurement by successive image analysis, Comput. Ind., Dec. 2005, Accessed: Oct. 19, 2021. [Online]. Available: https://dl.acm.org/doi/abs/10.5555/1672858.1672934.
[84] P. Ong, W.K. Lee, R.J.H. Lau, Tool condition monitoring in CNC end milling using wavelet neural network based on machine vision, Int. J. Adv. Manuf. Technol. 104 (1) (2019) 1369–1379, https://doi.org/10.1007/s00170-019-04020-6.
[85] P.K. Ambadekar, D.C.M. Choudhari, Application of Gray Level Co-occurrence Matrix as a feature extraction technique to monitor wear of cutting tool, (2018) 9.