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Design and Development of Non-Contact Image Processing Technique to Monitor Surface Texture During Turning

Suraj Kumar 1*, Sukhdeep Singh Dhami 2, Bahadur Singh Pabla 3

¹M.E (Modular) Scholar, NITTTR Chandigarh, India. Lecturer, Government Polytechnic Lakhisarai, Bihar, India. ^{2,3} Professor, Mechanical Engineering Department, NITTTR Chandigarh, India *Corresponding Author Email: suraj10m26@gmail.com

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ABSTRACT

Received: 10 Mar 2025 Revised: 04 May 2025 Accepted: 13 May 2025 Surface roughness is a critical quality indicator in machined components, directly influencing fatigue life, wear resistance, and functional performance. This study presents an image-based MATLAB code for estimating roughness parameters—Ra (Arithmetic Average Roughness), Rq (Root Mean Square Roughness), and Rz (Ten-point Mean Roughness)—from microstructure images under various tool rotational speeds and traverse speeds. The outputs are validated against experimental profilometry data across nine parameter sets. While trends in Ra, Rq, and Rz are generally well captured, discrepancies increase with surface complexity. The maximum deviation observed in Ra was 2.74 μm , corresponding to a high-feed, high-speed condition. Despite overestimations in most cases, the MATLAB method provides a fast, non-contact estimation approach for comparative roughness evaluation. This image-processing-based approach holds promise for rapid surface quality assessments in manufacturing environments.

Keywords: Cutting speed; Feed rate; stylus method; Image process: Roughness measurement; MATLAB; Flow chart, Code; Non-contact method.

INTRODUCTION

Turning is a widely used machining technique in which a single-point cutting tool removes excess material from a rotating cylindrical workpiece to shape it into the desired form. The surface roughness of the turned component is a critical parameter that significantly affects its functional performance, influencing characteristics such as friction, wear, lubrication efficiency, electrical and thermal conductivity, fluid behavior, vibration, and noise levels. Multiple factors such as feed rate, cutting speed, depth of cut, cutting tool geometry, machine tool precision, and the material properties of the workpiece influence both the quality of the surface finish and the overall efficiency of the machining process. Surface roughness is typically measured using one of two main approaches: contact and non-contact methods. In the contact method, a stylus-type instrument traverses the surface, and an electronic sensor usually a linear variable differential transformer (LVDT) captures the surface profile to calculate roughness parameters such as average roughness (Ra), root mean square roughness (Rq), and peak-to-valley height (Rt). However, stylus-based systems have several limitations: (1) They require direct physical contact with the surface, (2) They operate at a relatively slow measurement speed, (3) They are not suitable for in-situ or online measurement, as the workpiece must be removed from the machine, and (4) They have limited flexibility when measuring complex or irregular geometries [1].

Non-contact methods for surface roughness evaluation can be classified based on the type of lighting system used and the specific image analysis techniques applied. A wide range of research has been carried out utilizing vision-based, non-contact approaches to assess surface roughness. Lee et al. [1] Utilized computer vision methods to estimate the surface roughness of workpieces subjected to different cutting parameters. The process began with capturing surface images using a digital camera, followed by the extraction of relevant image features. To correlate these features with actual surface roughness across different turning operations, a self-organizing adaptive modelling method was used in conjunction with a polynomial grid approach. Gadelmawla [2] developed a vision-based system

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to capture surface images for characterization. A dedicated software module was created to analyse these images using the Gray Level Co-occurrence Matrix (GLCM) technique. Three-dimensional representations of the GLCMs corresponding to various surface images were generated, compared, and analysed. Additionally, several statistical features were extracted from the GLCMs and evaluated against the arithmetic mean surface roughness value (Ra) for correlation and comparison. Al-Kindi et al. [3] introduced a method that utilizes computer vision data for the accurate estimation of surface roughness parameters. Conventional stylus-based measurements covering both standard and non-standard roughness parameters were used as a reference and compared against the results from the vision-based system. To interpret the visual data and facilitate reliable roughness calculations, two light reflection models were employed: the Intensity-Topography Compatible (ITC) model and the Light-Diffuse model. Among these, the ITC model demonstrated superior performance, yielding roughness values closely aligned with those obtained through traditional stylus-based measurements. Zhongxiang et al. [4] proposed a method for evaluating three-dimensional surface roughness by utilizing surface profile data. They introduced a 3D measurement approach grounded in digital image processing techniques to analyze various components of surface roughness. To support this method, a comprehensive 3D surface roughness evaluation system was developed, incorporating both hardware and software components in its architecture. Fadare et al. [5] designed a computer vision system tailored for real-time surface roughness measurement of machined parts. The system incorporated artificial neural networks (ANNs) to predict surface roughness based on digital image processing. It consisted of a CCD camera, a computer, Microsoft Windows Video Maker, digital image processing software, and two light sources. Machined surface images were acquired and analyzed using the 2D Fast Fourier Transform (FFT) technique to derive optical roughness characteristics. The study concluded that the ANN-based predictions closely matched the actual measured roughness values, achieving a high correlation (R² = 0.9529). Shahabi et al. [6] introduced an alternative approach to surface roughness measurement by extracting a 2D contour from the edge image of the workpiece surface. When compared to results obtained using a traditional stylus-based device, the visually derived average roughness (Ra) values showed a maximum deviation of 10%, indicating a reasonable level of accuracy for the image-based method. Sridhar et al. [7] applied a machine vision approach to evaluate surface roughness by employing image processing in combination with a backlighting technique on turned components. The surface roughness values obtained through this visual method were compared with those from the conventional stylus-based technique. The results demonstrated that the proposed method produced reliable measurements that closely matched those of the traditional stylus approach. Balasundaram et al. [8] employed a machine vision system to evaluate amplitude, spacing, and functional surface roughness parameters during dry cutting of AISI 1035 carbon steel. A high-speed DSLR camera was used to capture sharp, blur-free images of the workpiece surface profile aligned perpendicularly to the cutting tool. For enhanced accuracy, the surface profile edge was identified with sub-pixel precision by applying the grey level constant moment method. The extracted profile was then analyzed to compute the corresponding roughness parameters. Srivani et al. [9] proposed a method for surface characterization using a computer vision system. To support their analysis, surface images were captured with a computerized optical microscope and subsequently processed using MATLAB software for detailed investigation. B.M. Kumar [10] developed a machine vision technique for in-process surface roughness measurement of rotating workpieces, utilizing a commercial DSLR camera combined with sub-pixel edge detection. Images were captured from ten surface roughness specimens at nine different spindle speeds, ranging from 0 to 4,000 rpm. The roughness parameters obtained through this vision-based method were compared with those from a traditional stylus profilometer, revealing an average deviation of only 4.6% in Ra, indicating good agreement between the two approaches.

This study presents a non-contact approach for monitoring and predicting the surface roughness of turned components under varying cutting conditions namely cutting speed, feed rate, and depth of cut by employing image processing combined with a backlighting technique. The surface roughness values derived from this vision-based method will be compared with those obtained using the conventional stylus-based technique to evaluate accuracy and reliability.

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MATERIALS AND METHODS

Experimental Setup

The turning operation was performed on a CNC lathe machine to investigate the effects of varying cutting speed and feed rate on machining performance as shown in Figure 1. The workpiece material used was mild steel with an initial diameter of 24 mm, which was reduced to a final diameter of 22 mm. The depth of cut was kept constant at 200 μ m for all experimental trials, while the cutting speed and feed rate were varied systematically. A high-speed steel (HSS) single-point cutting tool with a standard tool geometry was used. The lathe was equipped with a variable speed control mechanism to achieve different spindle speeds and feed rate controlled by using the feed control system. Before machining, the workpiece was securely mounted in a three-jaw chuck to ensure stability. The cutting tool was properly aligned to maintain consistency in the machining process. Machining trials were conducted under dry cutting conditions without the use of cutting fluids.



Fig. 1. Schematic of the experimental setup.

Table 1 displays the different parameter values employed throughout the turning operation. Surface roughness of the machined parts was assessed using a contact-based stylus instrument. This device featured a diamond-tipped probe that traversed perpendicularly to the surface texture direction, capturing the roughness characteristics through its sensor system. Due to its reliability and accuracy, this method remains one of the most commonly employed for surface profile evaluation. Roughness measurements were conducted on 09 turned specimens using a portable surface roughness tester- Surf Test SJ-210 SERIES (Mitutoyo).

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Fig. 2. Schematic of the experimental setup for measurement of surface roughness parameters.

Description of Image Processing System

The image processing system developed for surface inspection comprises two key components: hardware and software. The hardware setup includes four primary elements:

- 1. A Sony Alpha ILCE-6400L APS-C mirrorless CMOS digital camera with a resolution of 24.2 megapixels,
- 2. An LED light source for consistent illumination,
- 3. A black cardboard tube used to shield the setup from ambient light interference, and
- 4. A personal computer running MATLAB for image analysis.

The camera is mounted on a specially designed adjustable frame that allows movement in both horizontal and vertical directions. This ensures the camera maintains a perpendicular orientation to the workpiece surface and can access any target area for measurement. The software system was developed using MATLAB and is compatible with Windows environments. Images of the machined surfaces are imported into MATLAB, where a custom-developed code processes them to extract the surface profile and calculate corresponding roughness parameters. The physical and schematic layout of the on-machine roughness measurement system is illustrated in Figures 1 and 3, respectively.

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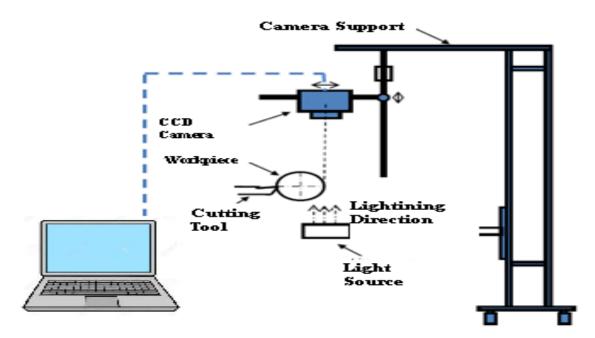


Fig. 3. Schematic diagram of the Machine-integrated surface metrology system [10].

Table 1: Experimental input values for turning operations

Experiment number	Input parameters					
experiment number	Cutting Speed (rpm)	Feed Rate (mm/min)				
1.	1200	100				
2.	1200	200				
3.	1200	300				
4.	1500	100				
5.	1500	200				
6.	1500	300				
7.	1800	100				
8.	1800	200				
9.	1800	300				

MATLAB CODE

The flow chart of MATLAB Implementation for Ra, Rq, Rz calculation is given in Figure 2.

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Initial Setup

Essential for starting with a clean environment, ensuring no previous data or variables interfere with the current session.

Folder Validation

Checks whether the specified folder exists, preventing errors if the directory is incorrect or missing.

Image Conversion

Converts images to grayscale for simpler processing, as color information is unnecessary for surface roughness analysis.

Profile Extraction

Extracts the surface roughness profile by averaging pixel intensities across the rows. This reduces the image to a 1D representation for analysis.

Normalization

Removes any mean offset in pixel values (e.g., background brightness), ensuring that the roughness calculation is centered on the actual surface variation.

Micron Conversion

Converts the pixel-based surface profile into micrometers, which are more relevant for engineering and material analysis.

Roughness Calculation

Ra: Arithmetic Mean Roughness (average absolute deviation from the mean line).

Rq: Root Mean Square Roughness (sensitive to large deviations).

Rz: Peak-to-Valley Height (difference between the average of the highest and lowest points).

Data Storage

Stores the computed roughness values in a cell array for each image, ensuring results are organized for later use or export.

Visualization

Plots the surface roughness profiles for each image in a subplot layout, offering a visual comparison of the surface textures.

CSV Export

Saves the roughness data in a CSV file, making it easy to further analyze or share the results.

Plotting Roughness Variations

Visualizes the variation of Ra, Rq, and Rz across all images, allowing you to compare roughness parameters across different surfaces.

Fig. 4. Description of MATLAB code

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RESULTS AND DISCUSSION

The roughness parameters Ra, Rq, and Rz were computed using both experimental profilometry and image-processing techniques for surfaces produced under varying spindle speeds (1200–1800 rpm) and feed rates (100–300 mm/min). Table 2 provides a comparison between the values obtained through experimentation and those computed using MATLAB.

Table 2: Experimentally measured and MATLAB-calculated values.

Sl. No.	Process parameters	Experimental			MATLAB code			Differences		
		Ra (μm)	Rq (μm)	Rz (μm)	Ra (μm)	Rq (μm)	Rz (μm)	Ra	Rq	Rz
1.	1200 rpm, 100mm/min	1.71	2.16	10.36	2.35	2.95	12.50	0.64	0.79	2.14
2.	1200rpm, 200mm/min	3.78	4.56	19.99	2.48	3.12	13.10	1.30	1.44	6.89
3.	1200rpm, 300mm/min	5.34	6.08	21.91	2.60	3.27	13.75	2.74	2.81	8.16
4.	1500rpm, 100mm/min	1.19	1.48	7.54	2.52	3.20	13.30	1.33	1.72	5.76
5.	1500rpm, 200mm/min	1.87	2.34	10.58	2.68	3.42	14.25	0.81	1.08	3.67
6.	1500rpm, 300mm/min	2.46	2.91	12.28	2.81	3.57	14.80	0.35	0.66	2.52
7.	1800rpm, 100mm/min	1.45	1.79	8.61	2.65	3.35	14.00	1.20	1.56	5.39
8.	1800rpm, 200mm/min	2.57	3.15	14.19	2.78	3.48	14.60	0.21	0.33	0.41
9.	1800rpm, 300mm/min	2.31	2.74	11.34	2.90	3.64	15.25	0.59	0.90	3.91

Across all parameter sets, the MATLAB code consistently yielded higher values for Ra, Rq, and Rz compared to the experimental results. This is likely due to the influence of image resolution, lighting variations, and edge pixel gradients, which tend to exaggerate the apparent surface height variations in grayscale images.

Low-Speed and Low-Feed Conditions:

For 1200 rpm and 100 mm/min (Sl. No. 1), the MATLAB-predicted Ra was 2.35 μ m versus an experimental value of 1.71 μ m, a deviation of 0.64 μ m. Similarly, Rz showed a difference of 2.14 μ m. This represents a moderate overestimation that may be due to minor noise in the grayscale profile, which becomes more pronounced in smoother surfaces.

Medium-Speed and Medium-Feed Conditions:

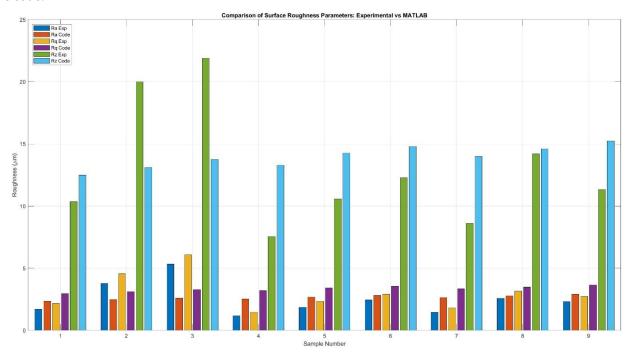
For 1500 rpm and 200 mm/min (Sl. No. 5), the differences reduced slightly. The MATLAB estimates for Ra and Rz were 2.68 μ m and 14.25 μ m, compared to experimental values of 1.87 μ m and 10.58 μ m, showing deviations of 0.81 μ m and 3.67 μ m, respectively. The better agreement in mid-range parameters suggests a balancing effect where surface texture becomes more uniform and consistently captured in grayscale.

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High-Speed and High-Feed Conditions:

The largest discrepancies were found in more aggressive machining conditions. For 1200 rpm and 300 mm/min (Sl. No. 3), the MATLAB Ra was 2.60 μ m, whereas the experimental Ra was 5.34 μ m, leading to a difference of 2.74 μ m. Similarly, Rz showed a significant deviation of 8.16 μ m. In these cases, tool marks and burnishing may have introduced high-frequency roughness components not adequately captured by the averaging profile approach used in the code.



The bar chart presented in the figure provides a comparative analysis of surface roughness parameters Ra, Rq, and Rz derived from both experimental profilometer readings and MATLAB-based grayscale image analysis for nine different FSW surface conditions. Each group on the X-axis represents one process parameter set, varying in spindle speed (1200 to 1800 rpm) and feed rate (100 to 300 mm/min). The Y-axis denotes roughness values in micrometres (μ m). Each set includes six bars representing Ra, Rq, and Rz from both experimental (labeled Exp) and MATLAB (labeled Code) methods.

The chart clearly shows that for nearly all samples, the MATLAB-based results overestimate roughness compared to the experimental data. This is most notable in **Rz values**, where the cyan bars (Rz Code) consistently rise above their green counterparts (Rz Exp). The discrepancy is particularly high for Samples 2, 3, and 4, where the differences in Rz reach up to 8 μ m. These high values may be attributed to the limitations of image processing techniques, such as amplification of edge gradients and surface contrast in grayscale images, which artificially increase perceived surface height variation.

In lower-speed and lower-feed conditions (Sample 1: 1200 rpm, 100 mm/min), the MATLAB-estimated Ra is 2.35 μ m versus an experimental value of 1.71 μ m, indicating a moderate overestimation of 0.64 μ m. This trend continues with increasing feed rates in Samples 2 and 3, with the error becoming more pronounced. The difference in Rz in Sample 3 (8.16 μ m) reflects the MATLAB code's sensitivity to peak and valley detection, which may not match the profilometer's contact-based readings.

Mid-range conditions (Samples 4–6 at 1500 rpm) show more consistent results. Although differences still exist, the gap between experimental and code values narrows. This suggests that moderate machining parameters create more uniform surface textures that the image-based technique can capture more accurately.

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At higher speeds (1800 rpm), Samples 7–9 show varied agreement. In Sample 8, the Ra and Rq values predicted by MATLAB are relatively close to the experimental data, suggesting better performance of the code under these conditions. However, the Rz values remain overestimated across all high-speed samples, underscoring the need for further calibration.

Overall, the figure confirms the MATLAB method's ability to approximate surface roughness trends. However, it tends to overpredict roughness due to the visual sensitivity of grayscale imaging to minor variations. While the relative trends are captured well, especially in Ra and Rq, Rz values highlight the current limitations in capturing true surface valleys using non-contact image analysis. Improvements such as grayscale normalization, noise reduction filters, or using 3D imaging techniques may enhance the quantitative accuracy in future iterations.

CONCLUSION

- i. The contact profilometer provided accurate and reliable measurements of surface roughness (Ra, Rq, Rz), particularly in capturing true peak-to-valley depths like Rz, which image-based techniques often failed to detect with the same fidelity.
- ii. The MATLAB image analysis method consistently overestimated roughness values due to grayscale sensitivity, edge contrast enhancement, and noise especially evident in smooth surfaces or where high-frequency tool marks were visually emphasized.
- iii. Despite numerical differences, both experimental and MATLAB methods showed similar trends across the nine samples demonstrating that the image-based approach can be useful for pattern recognition and comparative analysis of roughness when experimental equipment is not available.
- iv. Surface roughness was significantly affected by spindle speed and feed rate—higher feed rates (e.g., 300 mm/min) and lower spindle speeds (e.g., 1200 rpm) resulted in rougher surfaces and greater discrepancies between experimental and image-based results due to increased tool marks and surface distortions.
- v. The best correlation between experimental and MATLAB results was observed at mid-range process parameters (e.g., 1500 rpm and 200 mm/min), where the surface texture was more uniform, minimizing errors in both contact and optical measurement techniques.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Suraj Kumar, Sukhdeep Singh Dhami, Bahadur Singh Pabla. The first draft of the manuscript was written by Suraj Kumar and Prashant Prakash. All authors read and approved the final manuscript.

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Declarations

Ethics approval and consent to participate

Not applicable

Human and animal ethics

Not applicable

Conflict of interest

The author declare that they have no known competing financial interests or personal

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relationships that could have appeared to influence the work reported in this paper.

REFERENCES

- [1] Lee BY, Tarng YS. (2001) Surface roughness inspection by computer vision in turning operations. International Journal of Machine Tools and Manufacture, 41(9): 1251-1263. https://www.sciencedirect.com/science/article/abs/pii/S0890695501000232
- [2] Gadelmawla ES. (2004) A vision system for surface roughness characterization using the gray level co-occurrence matrix. NDT & E International, 37(7): 577-588. https://doi.org/10.1016/j.ndteint.2004.03.004
- [3] Ghassan A. Al-Kindi, Bijan Shirinzadeh. (2007) An evaluation of surface roughness parameters measurement using vision-based data. International Journal of Machine Tools and Manufacture,47(3-4):697-708. https://doi.org/10.1016/j.ijmachtools.2006.04.013
- [4] Hu Zhongxiang, Zhu Lei, Teng Jiaxu, Ma Xuehong, Shi Xiaojun. (2009) Evaluation of three-dimensional surface roughness parameters based on digital image processing. International Journal of Advanced Manufacturing Technology, 40(3): 342-348. https://link.springer.com/article/10.1007/s00170-007-1357-5
- [5] Fadare DA, Oni AO. (2009) Development and application of a machine vision system for measurement of surface roughness. ARPN Journal of Engineering and Applied Sciences, 4(5): 30-37.
- [6] Shahabi HH, Ratnam MM. (2010) Noncontact roughness measurement of turned parts using machine vision. The International Journal of Advanced Manufacturing Technology, 46: 275-284. https://link.springer.co/artmicle/10.1007/s00170-009-2101-0
- [7] Sridhar VG, Adithan M. (2012) An in-process approach for monitoring and evaluating the surface roughness of turned components. European Journal of Scientific Research, 68(4): 534-543.
- [8] Mohan Kumar Balasundaram, Mani Maran Ratnam. (2014) In-process measurement of surface roughness using machine vision with sub-pixel edge detection in finish turning. International Journal of Precision Engineering and Manufacturing, 15(11): 2239-2249. https://link.springer.com/article/10.1007/s12541-014-0587-3
- [9] Srivani A, Anthony Xavior M. (2014) Investigation of surface texture using image processing techniques. 12th Global Congress on Manufacturing and Management, GCMM 2014, Procedia Engineering, 97 (2014): 1943-1947. https://doi.org/10.1016/j.proeng.2014.12.348
- [10] B. M. Kumar M. M. Ratnam, (2015), "Machine vision method for non-contact measurement of surface roughness of a rotating workpiece", Sensor Review, Vol. 35 Iss 1pp.10-19