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Vision based prediction of surface roughness for end milling

Dhiren R. Patel [a,*], M.B. Kiran [b]

[a] Department of Mechanical Engineering, Indus Institute of Technology and Engineering, Indus University, Ahmedabad 382115, Gujarat, India
[b] Department of Industrial Engineering, School of Technology, PDPU, Gandhinagar 382007, Gujarat, India

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ABSTRACT

Measurement of surface roughness helps to assess the machined component's functionality. In the past three decades, several scientists have contributed to the computation of surface roughness. This research article deals with two distinct methods for prediction of surface roughness employing the surface profilometer and machine vision for AISI 1040 steel specimens prepared by varying cutting parameters of end milling viz. feed rates, speed and cutting depth. Using a surface profilometer, the surface roughness parameters are evaluated. At the other hand, the texture features were extracted using a Gray Level Co-occurrence Matrix Algorithm (GLCM) and a computer vision system. Correlations are formed among characteristics of machined surface and the texture feature such as contrast, entropy, energy, and homogeneity. The comparable findings revealed a maximum relative error of −8% using contrast and energy, − 11% using entropy and −10% using homogeneity.

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1. Introduction

Surface measurement is highly required in industries for technical advancement. Precise and quality surface in terms of accuracy and quick measurement is highly demanding in heavy industries. The surface texture of surface topography can be defined as the nature of the surface by characteristics like surface roughness and waviness. It is a very important factor to control friction. Machined surface influences dimensional accuracy and mechanical property, especially fatigue strength. Surface finish helps to determine fatigue life and corrosion life also [1–3].

Various studies, works and methods to quantify the roughness of the machined surface have been proposed [4–9] Surface measurement can be either contact-type measurement or non-contact type measurement method [10–12]. Even with high precision, various researches on non-contact type evaluation of surface roughness parameters using laser speckle, optical interference and light dispersion is carried out using a machine vision system and artificial intelligence due to the destructive nature of contact type surface measurement process [13–17].

Huaian et al. [18] worked on a new method to study roughness of a surface. This method uses no primary necessities to study uniform texture direction which extracts the current problems, like limited measurement range, intricate calculations etc. Accuracy of non-contact measurement is improved with this method. The purpose of this research is to investigate the relationship among roughness parameters and texture features of end-milled surfaces using non-contact type technique since it has certain focal points like high accuracy, high efficiency, immense flexibility, and non-contact in nature, the ability to acquire a considerable amount of data and excellent performance-price ratio compare to contact type measurement.

It is targeted towards the surface feature extraction using GLCM and correlating it to the parameter of surface roughness determined by a profilometer. Linear and non-linear regression models have been developed to predict arithmetical mean deviation (Ra). In the current research, the viability of detection models has been discussed.

2. Materials and methods

2.1. Experimental method

Surface finish is usually determined by the arithmetical mean deviation; Ra. Surface finish is a very important factor to determine the quality of the machining process. It also helps to control friction and determine the quality of joining between two surfaces.

* Corresponding author.
E-mail address: dhirenpatel85@gmail.com (D.R. Patel).

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Nomenclature

CCD	charge-coupled device	E	energy
GLCM	gray level co-occurrence matrix	ENT	entropy
Ra	arithmetic mean deviation of profile (μm)	H	homogeneity
VMC	vertical milling centre		
CON	contrast		

20 specimens of AISI 1040 steel was machined by the end milling process. These specimens were prepared at different machining parameters. Stylus instrument or surface profilometer consisting stylus made up of diamond probe which measures the parameters of the roughness of machined surfaces by moving it perpendicular to the direction of the surface [19]. Because of its benefits and producing a profile of an object in a well-defined path, it's been the most commonly used technique [20]. Roughness parameter of twenty milled surfaces has been measured using surface profilometer as shown in Fig. 1. Table 1 shows the conditions of the measurement via surface profilometer.

Table 1
Measuring conditions.

Type of Machining	VMC
Type of Measurement	Roughness
Calculation Standard	ISO'97/JIS'01/DIN
Length of Evaluation	8.00 mm
Speed of Measurement	0.6 mm/s
Cut-off	0.8 mm
Type of Filter	Gaussian
Range of Measurement	160 μm
Form Remove	Straight
Unit	mm/μm

2.2. Set-up of a machine vision system

The machine vision system has been used to capture machine surface images. High speed, high spatial resolution, and ease of operation make this method advantageous over conventional methods of measuring surface roughness. Also, it is extremely useful in the prediction of roughness in all modes viz. online, offline and in-process [21]. The system consisted of a CCD camera to capture the machined surface images under the ordinary lighting conditions as shown in Fig. 2. These images contain noises, uneven illumination and geometric image distortion. As it is difficult to eliminate these factors from a CCD camera, a specific algorithm is used to eliminate them, especially noises. To achieve precise and accurate information, it is important to eliminate these discontinuities from images.

The machine vision system is arranged such that it focuses on machined surface and capture corresponding images. Matlab is used to enhance images for further measurement using an image processing tool.

3. Result and discussion

In this section, results measured from surface profilometer and machine vision system will be compared.

3.1. Feature extraction

As shown in Table 2, four features were extracted from the surface image. These features are being used to correlate with the arithmetical mean deviation (Ra). Grey level intensity variations

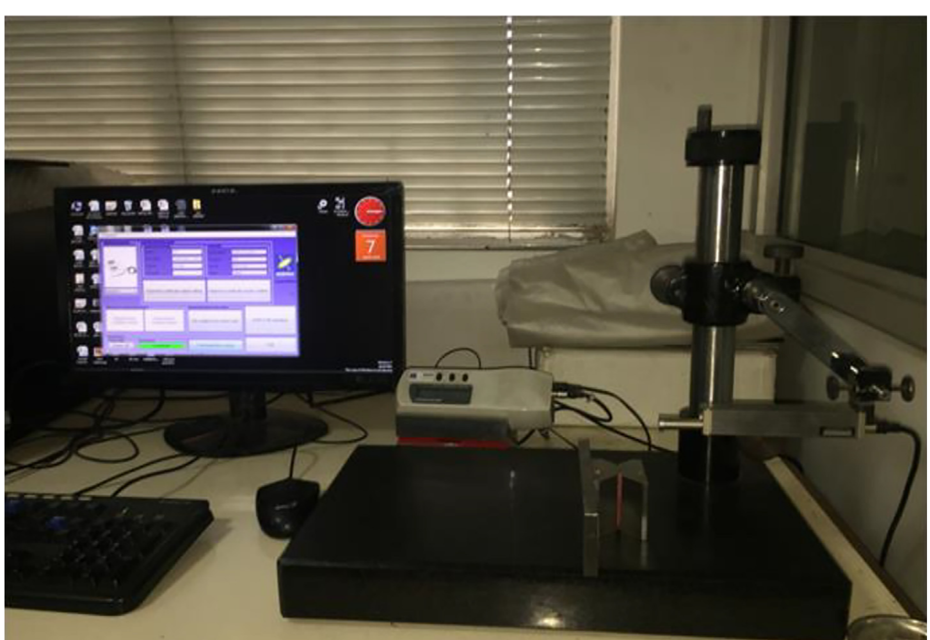

Fig. 1. Surface Profilometer – HANDYSURF 35-A/B.

Fig. 2. Setup of a machine vision system.

between pixels of surfaces are known as the contrast feature (F1). It is also sometimes termed as Inertia [22]. Difference between two neighbour pixel effects weight factor and consequently the contrast. Increase indifference also increases the contrast feature [23]. Uniformity of any image is measure by energy feature (F2). The measure of the extent of pixel pair repetition is defined as energy [24]. Disorder in an image is measured by entropy feature (F3). Uniformity in the image causes high entropy. In general words, entropy is inversely proportional to the energy. It also shows the amount of information needed for image compression. Loss of the information in a transmitted signal is measured by entropy [25].

Measurement of similarity in an image is given by homogeneity feature (F4). It is also termed as Inverse difference moment. The concentration of image elements at diagonal of the image is determined by homogeneity [24]. It is inversely proportional to the contrast feature and increases with increasing similar neighbour pixels [22].

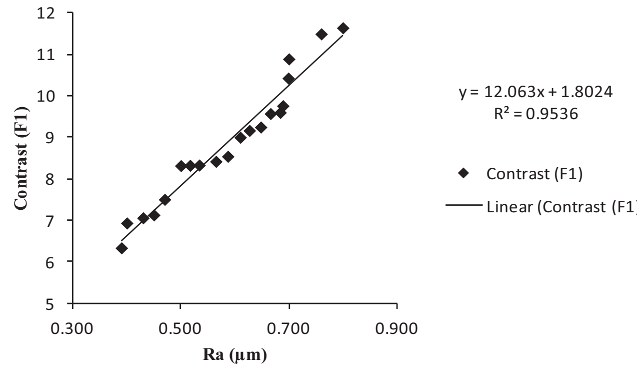

Fig. 3. Correlation trend between Contrast (F1) and measured arithmetical mean deviation Ra (µm).

3.2. Correlation

In this work, the correlation between these features and arithmetical mean deviation (Ra) has been plotted over a graph to determine the linear regression equation as shown in Figs. 3–6.

Regression equation can be used to determine the relationship between two or more variables [26]. The same method is used here to determine the relationship between the measured and predicted

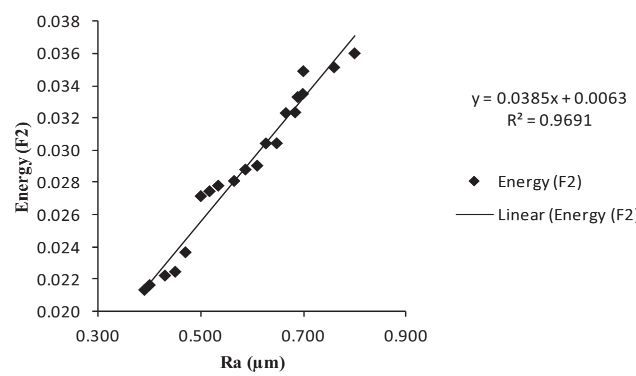

Fig. 4. Correlation trend between Energy (F2) and measured arithmetical mean deviation Ra (µm).

Table 2
Image texture features of milled components.

Specimen No.	Contrast (F1)	Energy (F2)	Entropy (F3)	Homogeneity (F4)
1	6.3276	0.0213	3.9628	0.2766
2	6.9264	0.0216	3.9608	0.2928
3	7.0514	0.0222	3.9325	0.2965
4	7.1210	0.0224	3.9090	0.2969
5	7.4950	0.0236	3.8648	0.3050
6	8.3075	0.0271	3.8285	0.3070
7	8.3145	0.0274	3.7976	0.3110
8	8.3216	0.0278	3.7954	0.3121
9	8.4103	0.0281	3.7841	0.3140
10	8.5323	0.0288	3.7414	0.3169
11	8.9909	0.0290	3.7377	0.3202
12	9.1552	0.0304	3.7368	0.3284
13	9.2369	0.0304	3.6931	0.3302
14	9.5615	0.0323	3.6838	0.3320
15	9.5897	0.0323	3.6746	0.3400
16	9.7500	0.0333	3.6293	0.3458
17	10.4153	0.0335	3.6274	0.3466
18	10.8780	0.0349	3.6144	0.3587
19	11.4808	0.0351	3.4573	0.3670
20	11.6280	0.0360	3.3584	0.3773

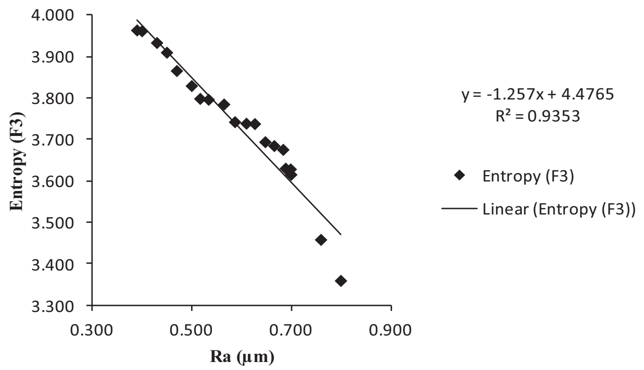

Fig. 5. Correlation trend between Entropy (F3) and measured arithmetical mean deviation Ra (μm).

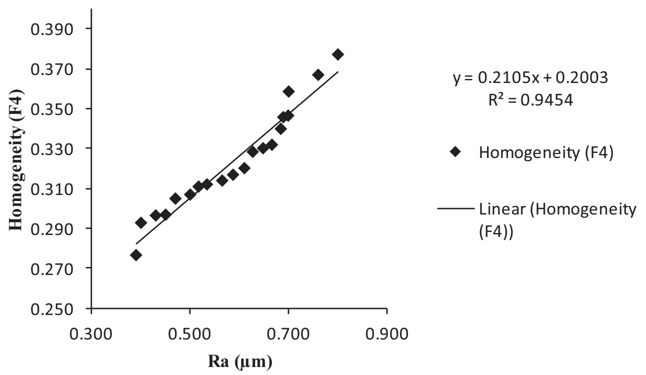

Fig. 6. Correlation trend between Homogeneity (F4) and measured arithmetical mean deviation Ra (μm).

value of surface features Contrast (F1), Energy (F2), Entropy (F3) and Homogeneity (F4). Results obtained from a machine vision system have a strong relationship with the average surface roughness value measured with a surface profilometer. Justification of the regression equation can be obtained from the coefficient of determination R^2. The high value of R^2 (near to 1) showed the outstanding relationship between the arithmetical mean deviation and extracted texture features.

The equation obtained for the Ra-Contrast relationship (CON) is,

$$CON = 12.063Ra + 1.8024 \tag{1}$$

Putting the value of Contrast feature obtained from the image processing method in Eq. (1), gives the predicted value of Ra for the surface of a different specimen. The maximum relative error of −8% and minimum relative error of 0% justify the reliability of this method and work.

Correlation between Ra and energy (E) is expressed as following Eq. (2),

$$E = 0.0385Ra + 0.0063 \tag{2}$$

The maximum relative error for the measured and predicted value of E is −8% while the minimum relative error is 0%.

The relationship between entropy (ENT) and Surface roughness is shown in Eq. (3),

$$ENT = -1.257Ra + 4.4765 \tag{3}$$

After determining the predicted value of surface roughness using this Eq. (3) for entropy, the maximum relative error is −11% and the minimum relative error is 0%.

Plot between homogeneity and surface roughness determines the following relationship between both, refer Eq. (4),

$$H = 0.2105Ra + 0.2003 \tag{4}$$

The maximum relative error between surface profilometer measured and machine vision system measured homogeneity is −10% and the minimum relative error is 0%.

The low relative error observed by the test, as shown in Table 3, confirms the good capability of the system developed to measure the surface roughness of the milled components. Better detection capability for linear detection model is found from the test results using texture features Contrast and Energy for the roughness of the milled workpiece surface.

4. Conclusion

Image processing techniques have been used in this work to extract surface features from end milling machined specimen

Table 3
Analysis of the relative error between actual and predicted roughness value.

	Contrast (F1)			Energy (F2)			Entropy (F3)			Homogeneity (F4)		
Measured Ra (μm)	Predicted Ra (μm)	Absolute Error	Relative Error	Predicted Ra (μm)	Absolute Error	Relative Error	Predicted Ra (μm)	Absolute Error	Relative Error	Predicted Ra (μm)	Absolute Error	Relative Error
0.390	0.375	0.015	4%	0.390	0.000	0%	0.409	−0.019	−5%	0.363	0.027	7%
0.400	0.425	−0.025	−6%	0.398	0.002	1%	0.410	−0.010	−3%	0.440	−0.040	−10%
0.430	0.435	−0.005	−1%	0.413	0.017	4%	0.433	−0.003	−1%	0.457	−0.027	−6%
0.450	0.441	0.009	2%	0.419	0.031	7%	0.451	−0.001	0%	0.459	−0.009	−2%
0.470	0.472	−0.002	0%	0.451	0.019	4%	0.487	−0.017	−4%	0.497	−0.027	−6%
0.500	0.539	−0.039	−8%	0.541	−0.041	−8%	0.515	−0.015	−3%	0.507	−0.007	−1%
0.517	0.540	−0.023	−4%	0.549	−0.032	−6%	0.540	−0.023	−4%	0.526	−0.009	−2%
0.534	0.540	−0.006	−1%	0.558	−0.024	−5%	0.542	−0.008	−1%	0.531	0.003	1%
0.565	0.548	0.017	3%	0.566	−0.001	0%	0.551	0.014	3%	0.540	0.025	4%
0.587	0.558	0.029	5%	0.584	0.003	0%	0.585	0.002	0%	0.554	0.033	6%
0.610	0.596	0.014	2%	0.590	0.020	3%	0.588	0.022	4%	0.570	0.040	7%
0.627	0.610	0.017	3%	0.626	0.001	0%	0.588	0.039	6%	0.609	0.018	3%
0.648	0.616	0.032	5%	0.626	0.022	3%	0.623	0.025	4%	0.617	0.031	5%
0.666	0.643	0.023	3%	0.675	−0.009	−1%	0.631	0.035	5%	0.626	0.040	6%
0.684	0.646	0.038	6%	0.676	0.008	1%	0.638	0.046	7%	0.663	0.021	3%
0.689	0.659	0.030	4%	0.701	−0.012	−2%	0.674	0.015	2%	0.691	−0.002	0%
0.699	0.714	−0.015	−2%	0.706	−0.007	−1%	0.675	0.024	3%	0.695	0.004	1%
0.700	0.752	−0.052	−7%	0.743	−0.043	−6%	0.686	0.014	2%	0.752	−0.052	−7%
0.760	0.802	−0.042	−6%	0.749	0.011	1%	0.811	−0.051	−7%	0.792	−0.032	−4%
0.800	0.815	−0.015	−2%	0.772	0.028	4%	0.889	−0.089	−11%	0.841	−0.041	−5%

and Artificial Intelligent technique for classification of image texture. Linear regression modeling used to develop the mathematical relation between extracted image features; contrast (CON), energy (E), entropy (ENT) and homogeneity (H); and arithmetical mean deviation (Ra) measured by a profilometer. This linear regression equation from the plot between Ra and image features has been used to predict the value of Ra by putting the value of image features. Statistical analysis shows that the maximum relative error of -8% using contrast and energy, -11% using entropy and -10% using homogeneity between contact type and proposed non-contact type assessment technique. Low values of relative error conclude to the point of effective roughness prediction of milled surfaces by non-contact approach.

CRediT authorship contribution statement

Dhiren R. Patel: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **M.B. Kiran:** Supervision, Project administration.

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.

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