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Noncontact Surface Roughness Measurement of Machined Surfaces Using Grinding Process by the Application of Digital Image Magnification

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Abstract

In today's competitive world, manufacturing requires fast and accurate systems that provide the feedback to control the machining process and improve product quality and productivity. One of the parameters to be controlled in machining is surface finish, which is a vital criterion in the performance and utility of industrial products. The computer vision based system is used to analyze the pattern of scattered light from the surface to assess the surface roughness of the component. In recent years the advent of high speed digital computers and vision systems has made image analysis easier and flexible. Unlike the stylus instruments, the computer vision systems have the advantages of being non-contact and are capable of measuring an area of the surface rather than a single line which makes it a 3D evaluation. In this research work, a machine vision system has been utilized to capture the images of ground surfaces and then the quantification of digital pictures of ground surfaces is done. Subsequently, original images of ground surfaces have been magnified using cubic convolution, Nearest Neighbor and Bilinear interpolation techniques. Then the optical surface roughness parameter Ga has been estimated for all the captured surface images and for the magnified quality improved images. Finally, a comparison has been done to find correlation between the magnification factor and optical surface roughness parameter Ga for the three interpolation algorithms.

Keywords: Bilinear interpolation, cubic convolution, magnification factor, surface roughness.

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INTRODUCTION

Surface roughness is usually a detrimental by-product of all machining processes. Surface roughness also affects several functional attributes of parts, such as friction, wear and tear, light reflection, heat transmission, ability of distributing and holding a lubricant. In manufacturing, the surface finish is adopted as finger print of the machining process.[1,2] Surface finish measurement is also useful in providing an index of process stability. The proper functioning of a machined part is in many instances largely dependent on the quality of its surface. Surface roughness is one of the key factors for overall work piece quality evaluation. The study of surface texture is commonly referred to as Surface Metrology. It involves the measurement and characterization of surfaces and their relationship to the manufacturing process that generated the part and functional performance measures of the component. Surface analysis relies on the assumption that the surface geometry irregularities can be used as a fingerprint of the process and machine tool.[3] The traditional method of surface roughness measurement is done using the stylus instrument, which correlates the motion of a diamond-tipped stylus to the roughness of the surface under investigation. This method is widely accepted and has been used for many decades in the manufacturing industry.[4] Although widely accepted, these instruments have several limitations such as low speed measurement, requiring direct physical contact, vibration-free environment, etc. In addition, the resolution and the accuracy of the instrument depends mainly on the diameter of the tip of the probe of the stylus device. Stylus instruments are largely affected by system error, when the surface roughness falls below 2.5 μm. Besides, the instrument readings are based on a limited number of line samplings, which may not represent the actual characteristics of the surface.[5,6] This kind of deviation may cause serious errors in the surface quality assessment especially when the surface profile is periodic. Stylus instruments have limited flexibility in handling the different geometrical parts to be measured.[7,8] Because of these drawbacks, contact type instruments are not suitable for high-speed automated inspection. The demand for improved flexibility, productivity, and product quality in modern machining industry has necessitated the need for high-speed, noncontact and on-line monitoring and measurement of surface roughness of machine components. Measurement of surface roughness using Machine vision methods are being developed worldwide due to their intrinsic advantages, including non-contact measurement, high information content, rapid measurement, and surface measurement capability. With the advent of high-speed digital computers and powerful high speed vision systems image analysis have become easier, faster and more flexible. Numerous researchers have so far used the vision system for grabbing images of machined surfaces, improving their quality by pre-processing and then analyzed them for assessment of surface finish with a reasonable success.

Light scattering was introduced as a practical tool for Surface roughness measurement. With the advent of automation, surface characterization needs to be totally computerized so that the task of inspection is greatly simplified and free from human error. A large number of industrial activities including delicate electronics component manufacturing, quality textile production, glass manufacturing, metal product finishing, printing products, granite quality inspection, integrated circuits(IC) manufacturing and many more, have benefited from the application of machine vision technology. Image processing and machine vision technology improves productivity and quality management and provides a competitive advantage to industries that employ this technology. New software and hardware with more powerful functions are emerging continually in the market. Machine Vision typically employs a camera, a frame grabber, a digitizer and a processor for inspection tasks where precision, repetition and/or high speed are needed. The histograms of the surface image have been utilized to characterize surface roughness and quality. Machine vision allows the assessment of surface roughness without touching or scratching the surface. It provides the benefits of a measurement process for 100% inspection and the flexibility for measuring the part under test without fixing it in the precise position. Compared to the stylus based methods that trace the surface roughness in one dimension, vision system can generate numerous readings of a two dimensional surface in a given time, and this makes the surface roughness evaluation more reliable. Using machine vision, it is possible to characterize, evaluate and analyze the area of the surface of machined components, which makes it a 2D evaluation.[7] Machine vision systems play an important role in the monitoring and control of automated machining systems. It has generated a great deal of interest in the manufacturing industry. Researchers have shown that the application machine vision has the advantage of being non-contact and has well faster than the contact methods.[9] Several investigations have been carried out using the non-contact optical methods for the assessment of surface roughness. Most of the methods are based on statistical analyses of the gray-scale images in the spatial domain. The intensity histograms of the surface image have been utilized to characterize surface roughness and quality.[10] The authors utilized statistical parameters, derived from the grey level intensity histogram such as the range and the mean value of the distribution and correlated them with the centre line average (R_a) value measured with a stylus instrument. Statistical methods such as co-occurrence matrix approach, the amplitude varying rate statistical approach, and run length matrix approach have also been used to compare the texture features of milled, shaped and ground surfaces.[6] They correlated the mean value of the intensity distribution with the Ra value obtained from stylus instrument to determine the surface roughness of the machined components. Hoy and Yu.[11] applied the algorithm of Luk and Huyuh to characterize surface roughness using the Fourier transform in the frequency domain. M. Gupta et al.[12] tried to characterize the surface roughness by calculating the intensity of the light reflected from the machined surface. They conducted experiments both on stationary and rotating surfaces and calculated standard deviation, arithmetic mean along with root mean square (RMS) values of the gray level intensity distribution. They proposed two parameters R1 and R2, which are calculated by dividing standard deviation with RMS and standard deviation with arithmetic mean, respectively. They also tested the sensitivity of these parameters to the differences in surface roughness, ambient light and spindle speed and shown that these vision parameters can discriminate the different surface roughness heights and insensitive to ambient lighting and speed rotation. Gary Wagner[13] described geometric search as the most accurate and appropriate method for improving the quality of images by enhancing the edges in image processing. In their work, surface finish could be predicted with a reasonable degree of accuracy by taking the acceleration of radial vibration of the tool holder as a feedback. Gopalakrishnan[14] studied the principle of fractal geometry and image processing techniques for area based surface finish monitoring system. Manoj Kumar Biswas et al.[15] presented fractal dimension as an important parameter in the estimation of surface roughness. Pal and Chakraborty[16] predicted surface roughness by considering main cutting force, feed force, cutting speed, feed, and depth of cut as input parameters for the artificial neural network. It was observed that the model with cutting forces as additional input yielded better results. Ho S.Y. et al.[17] used an adaptive neuro-fuzzy inference system (ANFIS) to analyze surface images in turning for calculating the arithmetic average of gray levels. Takeyama and Lijama[18] studied the surface roughness on machining of Glass Fiber Reinforced Polymer (GFRP) composites. The authors observed that higher cutting speed produce more damages on the machined surface. The authors also studied the machinability of FRP composites using the ultrasonic machining technique. Sodhi and Tiliouine[19] have introduced a parameter called the optical roughness indicator, which indicates the change in size of the illuminated area to determine the surface roughness of grinded materials. They have used the speckle pattern observed by using a laser beam on a machined surface. Priya and Ramamoorthy[20] estimated and analyzed the optical roughness parameters of the machined surfaces by deliberately keeping them at various angles inclined to the horizontal and capturing the images using a machine vision system. Du-Ming Tsai et al.[21] proposed a machine vision system for the classification of castings. The method of assessing surface quality is based on the two-dimensional Fourier Transform of a cast surface in both gray level image and binary image. They implemented Bays classifier and neural network classifier for roughness classification.

Interpolation is the process of estimating the intermediate values of a continuous event from discrete samples.[22] Interpolation is used extensively in digital image processing to magnify or reduce images and to correct spatial distortions. The major limitation in most of the digital image magnification techniques is lack of any new information to the original image.[23] Absence of high spatial frequency components due to lack of information is responsible for the perceptible degradation of magnified images, which are reflected in blurred edges. Interpolation methods are usually employed in magnification of digital images. One of the best interpolation schemes namely cubic convolution developed by Keys[22] approximates the ideal since function by truncating it and this non-ideal interpolation cuts some high frequencies, which are present in the original image, leading to band limiting effects on the high resolution image. In contrast to cubic convolution, the cubic spline method generates a better high-resolution version of an image, but it is much more cumbersome to compute. Edge blurring is even more severe with other magnification techniques. There have been several attempts in the past for improvements to achieve image magnification. Hewlett Packard[24] has reported an approach in this regard which is patented by them. Most of these methods use edge information at the low resolution of the original image to be interpolated.

Here in this work an attempt is made to digitally magnify the surface image. To test the quantification parameters evaluated using this method, a comparative study has been presented with the mechanical stylus parameters with complete analysis. It has been finally established that this digital magnification followed by qualitative evaluation of surface images could be very well used for ground surfaces.

EXPERIMENTAL PROCEDURE

Experiments were carried out in a precision surface-grinding machine to conduct an in-process inspection by the proposed method. Specimens were prepared with different surface roughness by grinding. The factorial designs of experiments were conducted with three levels for each factors (speed, feed and depth of cut) with a constant cross feed. The cutting parameters used in the experiments are tabulated in Table 1.

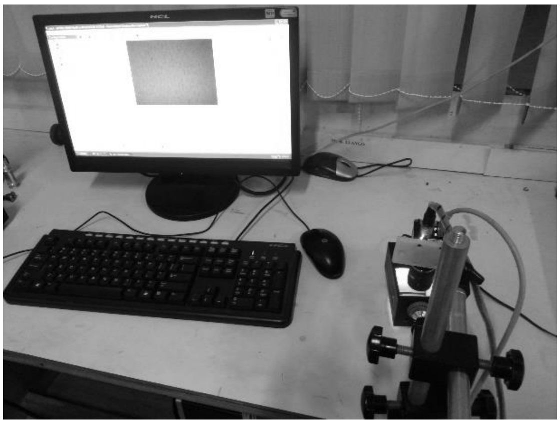

Fig. 1. *Experimental Setup.*

The basic experimental set-up consists of a vision system (CCD camera: Blue Cougar

– X125Ag Matrix Vision) and an appropriate Axial Diffuse Illuminator lighting arrangement shown in Figure 1. The experiment was carried out on a precision surface grinding machine. The experiments were carried out using flat EN8 mild steel specimens manufactured by grinding process. The chemical composition of the work material is given in Table 2. In this work, EN8 mild steel grade SAE 1038 material is used for conducting the surface finish studies due to its wide range of application requiring higher strength such as in shafts, gears, stressed pins, studs, bolts, keys etc. EN8 is a very popular grade and is readily machinable in any condition. The specimens were placed on a flat surface and the images were taken. The vision system consisted of a CCD camera, image processing software, a computer, an image processing board and a video monitor. The images of the surface of the workpiece to be measured were captured by the camera and the frame grabber card digitized the image and stored it in the frame buffer. Each pixel had a certain illumination intensity value. The grey scale analysis technique has been typically used for processing and analyzing the image. The digital image was then transferred to a display subsystem.

Table 1. *Machining Parameters Used for Grinding and the Roughness Values.*

Test no.	Speed	Feed	Depth of cut	G_a, Optical	Ra, Stylus
(rpm)	(mm/rev)	(mm)	Parameter	Parameter	
1	900	0.2	0.1	6.1881	0.61
2	900	0.3	0.1	7.3122	0.66
3	900	0.1	0.2	7.4187	0.53
4	900	0.3	0.2	6.9863	0.43
5	900	0.2	0.3	7.4187	0.7
6	900	0.3	0.3	6.9945	0.92
7	900	0.1	0.4	7.701	0.69
8	900	0.3	0.4	7.5311	1.05
9	1800	0.05	0.2	6.6964	0.72
10	1800	0.05	0.3	7.5216	1.16
11	1800	0.03	0.3	7.3043	0.32
12	1800	0.04	0.1	7.8384	0.3
13	1800	0.04	0.2	7.8554	0.45
14	1800	0.02	0.3	5.9265	0.64

Table 2. *Composition of Workpiece.*

Material	**Grade**	**C (%)**	**Si (%)**	**Mn (%)**	**Co (%)**	**Yield strength (MPa)**	**Tensile strength (MPa)**	**Elongation (%)**
EN8	SAE 1038	0.35	0.10	0.6	0.06	280	550	16

MAGNIFICATION OF DIGITAL IMAGES

Magnification of digital images is basically a problem of brightness interpolation in the input image which is also a low resolution image. It starts with the geometric transformation of the input pixels which are mapped to a new position in the output image. A geometric transform is a vector function T that maps the pixel (x, y) to a new position (x', y'). T is defined by its two component equations:

$$x' = T_x(x, y), y' = T_y(x, y) \qquad (1)$$

Eq. (1) has been assumed to be planar transformation, which is accomplished and new co-ordinate point (x', y') is obtained. The position of the point generally does not fit the discrete raster of the output image and the collection of transformed points provides the samples of the output image with non-integer co-ordinates.

Values on the interior grid are needed, and each pixel value in the output image raster can be obtained by brightness interpolation of some neighboring non-integer samples.

The brightness interpolation problem is usually expressed in a dual way by determining the brightness of the original point in the input image that corresponds to the point in the output image lying on the discrete raster.

Suppose that the brightness value of the pixel (x', y') in the output image needs to be computed, where x' and y' lie on the discrete raster (integer numbers). The co-ordinates of the point (x, y) in the original image can be obtained by inverting the planar transformation in Eq. (1)

$$(x, y) = T^{-1}(x', y')$$

Generally, the real co-ordinates after inverse transformation do not fit the input image discrete raster, and so brightness is not known. The only information available about the originally continuous image function $f(x, y)$ is its sampled version $g_s(l\Delta x, k\Delta y)$. To get the brightness value of the point (x, y) the input image is resampled. Let the result of the brightness interpolation be denoted by $f_n(x, y)$, where n distinguishes different interpolation methods. The brightness can be expressed by the convolution equation:

$$f_n(x, y) = \sum_{i=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} g_s(l\,\Delta x, k\Delta y) h_n(x - l\Delta x, y - k\Delta y) \qquad (2)$$

The function h_n is called the interpolation kernel and it is defined differently for different interpolation schemes. It denotes the neighborhood of the point at which brightness is desired. Usually, only a small neighborhood is used, outside which h_m is zero.

Therefore, the brightness interpolation is, in effect; input image resampling which generates the high resolution version of the input image. Three interpolation methods, which are used quite extensively for digital image magnification, are Nearest neighbor interpolation, Bilinear interpolation and Bicubic interpolation. In this paper, all these three interpolation methods have been employed to achieve the digital image magnification. Nearest neighbor interpolation algorithm is the most basic one, which needs the minimum processing time of all the interpolation methods, since it only considers one pixel that is closest to the interpolated point. Consequently, this results in making each pixel bigger. Bilinear interpolation considers the closest 2×2 neighborhood of known pixel values surrounding the unknown pixel. It then takes a weighted average of these 4 pixels to arrive at its final interpolated value. This results in much smoother looking images than nearest neighbor. In contrast to bilinear algorithm, Bicubic interpolation method considers the closest 4×4 neighborhood of known pixels that result to the total of 16 pixels. Since these are at various distances from the unknown pixel, closer pixels are given a higher weighting in the calculation. Bicubic interpolation method produces noticeably sharper images than the other two methods and also provides the ideal combination of processing time and output quality. Exhaustive treatment of concepts and mathematical description for these interpolation techniques are originally proposed by Keys.[22]

SURFACE ROUGHNESS ESTIMATION

The surface roughness R_a is the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|y_i|$$

where y_i is the height of roughness irregularities from the mean value and n is the number of sampling data. This parameter Ra is widely used by all the researchers and industrial users.

In the case of Machine Vision, optical roughness parameter G_a is used to estimate surface roughness. G_a is the arithmetic average of grey level intensity values

$$G_a = \frac{1}{n}\sum_{i=1}^{n}|g_i|$$

where g_i is the difference between the grey level intensity of individual pixels in the surface image and the mean grey value of all the pixels under consideration. The grey level average (G_a) has been calculated for all the surfaces of the prepared ground specimens after capturing the images of the surfaces. These G_a values have been calibrated with the corresponding R_a values measured using a stylus profilometer.

Earlier research work[25] carried out on roughness evaluation of surfaces using machine vision involved correlating the spectra of such surfaces to the roughness values and these have been shown to follow power law behavior.

Profile of such surfaces were shown to be self-affined which implies that when magnified, increasing details of roughness emerge and appear similar to the original profile. In this paper an attempt has been made to correlate the grey level average (G_a) values obtained from the images with their respective surface roughness and study the behavior of such a correlation at various degrees of image magnification for the three different interpolation techniques.

Consequently, images of workpieces captured by machine vision were magnified by factors 2, 4, 8 and 16 using the three different magnification techniques.

The feature of the image under study, G_a, was extracted and a correlation between G_a and surface roughness R_a was established on the basis of data given in Tables 3–5 (for three different interpolation techniques). Based on the values of correlation coefficient so obtained, plots have been drawn between the magnification factor and correlation coefficient from the data and are shown in Figure 2 for three different interpolation techniques.

Table 3. *Variation of G_a with Varying Magnification Factors by Nearest Neighbor Interpolation.*

G_a (1X)	G_a (2X)	G_a (4X)	G_a (8X)	G_a (16X)	R_a (mm)
6.9863	8.2645	8.2646	8.2646	8.2647	0.43
7.4187	8.6619	8.6620	8.6621	8.6622	0.53
7.3122	8.8110	8.8111	8.8112	8.8112	0.66
7.7010	8.8912	8.8913	8.8914	8.8915	0.69
7.4187	8.7527	8.7528	8.7529	8.7529	0.7
7.5311	8.8213	8.8214	8.8215	8.8215	1.05
7.5216	8.9132	8.9133	8.9134	8.9135	1.16

Table 4. *Variation of G_a with Varying Magnification Factors by Bilinear Interpolation.*

G_a (1X)	G_a (2X)	G_a (4X)	G_a (8X)	G_a (16X)	R_a (mm)
6.9863	7.7917	7.8316	7.8413	7.8437	0.43
7.4187	8.0161	8.1587	8.1699	8.1727	0.53
7.3122	8.2524	8.2780	8.2899	8.2929	0.66
7.7010	8.4823	8.5126	8.5215	8.5236	0.69
7.4187	8.1461	8.1856	8.1982	8.2013	0.7
7.5311	8.1011	8.2329	8.2875	8.3011	1.05
7.5216	8.3939	8.4359	8.4549	8.4813	1.16

Table 5. *Variation of G_a With Varying Magnification Factors by Bicubic Interpolation.*

G_a (1X)	G_a (2X)	G_a (4X)	G_a (8X)	G_a (16X)	R_a (mm)
6.9863	8.0609	8.0695	8.0798	8.0697	0.43
7.4187	8.4348	8.4416	8.4417	8.4417	0.53
7.3122	8.5584	8.5646	8.5647	8.5651	0.66
7.7010	8.7247	8.7291	8.7292	8.7293	0.69
7.4187	8.4911	8.4984	8.4985	8.4990	0.7
7.5311	8.5036	8.5137	8.5138	8.5138	1.05
7.5216	8.6982	8.7771	8.9106	9.7060	1.16

DISCUSSION OF RESULTS

Based on the interpolation algorithms, the digital images of machined work pieces have been magnified for a wide range of magnification index ranging from 2X to16X going in steps, suitable for future task of determining surface roughness and also to assess the effectiveness of improvement scheme once applied to them.

Cubic convolution remains as one of the best methods for magnification of digital images in terms of preserving edge details when compared to other methods, the blurring of edges has been found to be reduced substantially.[22] It is a great advantage, as the edges influence the image parameters decisively, and effective preservation of edges is essential for all image-processing applications including surface roughness determination. The computational simplicity offered by cubic convolution method cannot be abandoned for the slightly better result given by cubic spline method. Basically the accuracy of the interpolation technique to provide image magnification depends on its convergence rate. Cubic convolution interpolation algorithm[22] offers a O(h3) convergence rate, while cubic spline has a fourth order convergence rate, i.e. O(h4). Higher convergence rate can be achieved by altering the conditions on interpolation kernel, which in turn demands higher computational effort to derive interpolation coefficients.

So there is a tradeoff between accuracy offered by an interpolation technique and efficiency in terms of computational effort it requires. Moreover, it is implemented quite easily by modern digital computers and image processors. The present algorithm is the optimal choice, although it cannot prevent the perceptible degradation of edges fully. Some amount of blurring can be seen in every magnified image.

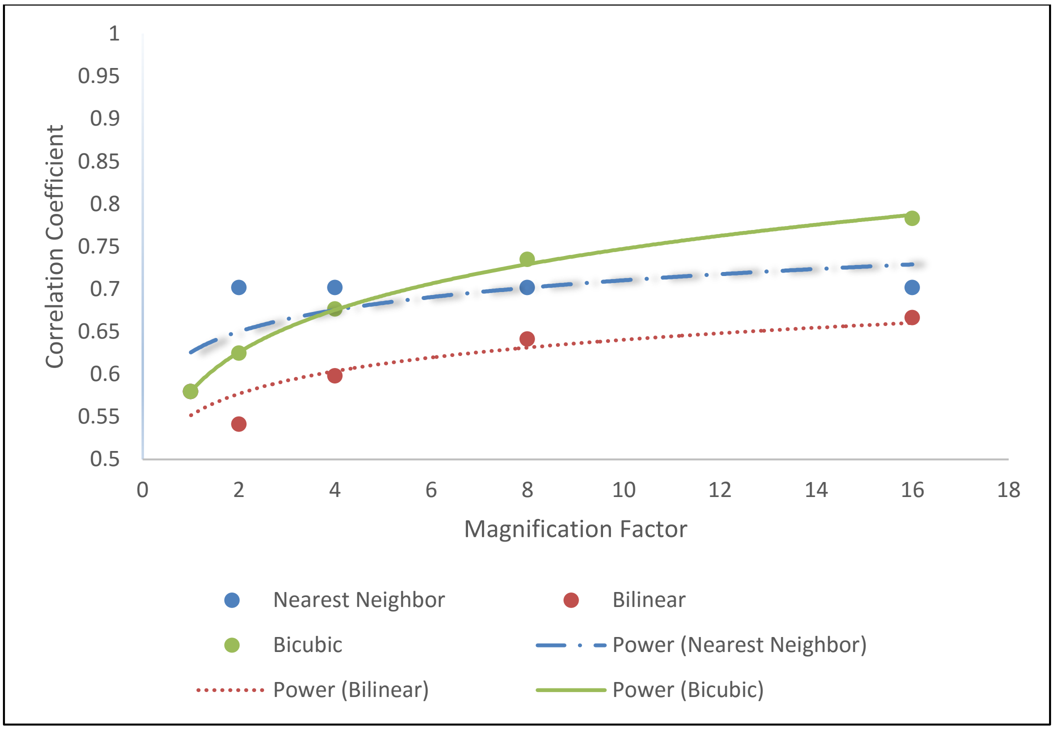

Fig. 2. *Variation of Correlation Coefficient with Magnification Factor for Three Interpolation Algorithms.*

Finally, as seen from the plots in Figure 2, there is an increase in the correlation coefficient with the magnification index and this increment is more marked in the case of cubic convolution method compared to nearest neighbor and bilinear algorithms. As mentioned earlier, owing to simplicity and limitations in the case of Nearest neighbor and Bilinear interpolation methods, magnification algorithm becomes increasingly ineffective with magnification index. This in turn means that magnified images of ground surfaces in the case of Nearest neighbor and Bilinear interpolation methods, cannot predict the actual or 'true' surface characteristics of a very small region of the image (which is subject to magnification), as compared to the Bicubic interpolation algorithm, since large and irregular surface feature variation renders it difficult for the magnification algorithms to interpolate the brightness value of a pixel from that of its adjacent pixels correctly. Whereas Bicubic interpolation method produces noticeably sharper images than the previous two methods, and perhaps the ideal combination of processing time and output quality helps magnification scheme to predict values which are remarkably closer to the actual ones. It has also been observed that the plots in Figure 2 follow the power law.

CONCLUSION

The present work clearly indicates that the Machine vision approach can be used to evaluate the surface roughness of machined surfaces. Cubic convolution interpolation method proved to be the optimal choice for magnification of digital images. The calculation of G_a, optical roughness value, from these magnified and improved images of the cubic convolution algorithm had a better correlation (i.e. higher correlation coefficient) with the average surface roughness (R_a) measured for the ground components, when compared to other two methods,. It can also be inferred that this Cubic convolution algorithm provides a better O(h3) convergence rate scheme of optical roughness estimation, indicating its effectiveness in application to the measurement using machine vision system.

REFERENCES

1. Fadare D.A., Oni A. Development and application of a machine vision system for measurement of surface roughness, *ARPN J Eng Appl Sci*. 2009; 4(5).
2. Kim H.Y., Shen Y.F., Ahn J.H. Development of a surface roughness measurement system using reflected laser beam, *J Mater Process Technol*. 2002; 662–7p.
3. Whitehouse D.J. Review article – surface metrology, *Measur Sci Technol*. 1997; 8: 955–72p.
4. Thomas T.R., *Rough Surface*. London: Imperial College Press; 1999.
5. Younis M.A. On line surface roughness measurements using image processing towards an adaptive control, *Comput Ind Eng*. 1998; 35(1–2): 49–52p.
6. Venkata Ramana K., Ramamoorthy B. Statistical methods to compare the texture parameter of machined surfaces, *Pat Recogn*. 1996; 29(9): 1447–59p.
7. Kiran M., Ramamoorthy B., Radhakrishnan V. Evaluation of surface roughness by vision system, *Int J Mach Tools Manuf*. 1998; 38(5): 685–90p.
8. Lee B.Y., Tarng Y.S. Surface roughness inspection by computer vision in turning operations, *Int J Mach Tools Manuf*. 2001; 41: 1251–63p.
9. Al-Kindi G.A., Baul R.M., Gill K.F. An application of machine vision in the automated inspection of engineering surfaces, *Int J Prod Res*. 1992; 30(2): 241–53p.
10. Luk F., Huynh V., North W. Measurement of surface roughness by a machine vision system, *J Phys E Sci Instrum*. 1989; 22: 977–80p.
11. Dep H., Yu F. Surface quality assessment using computer vision methods, *J Mater Process Technol*. 1991; 28: 265–74p.
12. Gupta M., Raman S. Machine vision assisted characterization of machined surfaces, *Int J Prod Res*. 2001; 39(4): 759–84p.
13. Wagner G., Geometric search: accurate machine vision in challenging conditions, *Images Rep Autumn*. 2000; 32–3p.
14. Zhang G., Gopalakrishnan S. Fractal geometry applied to on-line monitoring of surface finish, *Int J Mach Tools Manuf*. 1996; 36(10): 1137–50p.
15. Biswas M.K., Ghose T., Guha S., *et al*. Fractal dimension estimation for texture images: a parallel approach, *Pat Recog Lett*. 1998; 19(3): 309–13p.
16. Pal S.K., Chakraborty D., Surface roughness prediction in turning using artificial neural network, *Neur Comput Appl*. 2005; 14(1): 319–24p.
17. Lee K.-C., Ho S.-J., Chen S.S. Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system, *Int J Mach Tools Manuf*. 2002; 42(13): 1441–6p.
18. Takeyama H., Lijama N. Machinability of glass fibre reinforced plastics and application of ultrasonic machining, *Ann CIRP*. 1988; 97(1): 93–6p.
19. Sodhi M.S., Tiliouinet K. Surface roughness monitoring using computer vision, *Int J Mach Tools Manuf*. 1996; 36: 817–28p.
20. Priya P., Ramamoorthy B. The influence of component inclination on surface finish evaluation using digital image processing, *Int J Mach Tools Manuf*. 2007; 47(3–4): 570–9p.
21. Tsai D.-M., Tseng C.-F. Surface roughness classification for castings, *Pat Recogn*. 1999; 32: 389–405p.
22. Keys R.G. Cubic convolution interpolation for digital image

processing, *IEEE Trans ASSP*. 1981; 29(6): 1153–60p.

23. Kumar R., Kulashekar P., Dhanasekar B., *et al*. Application of digital image magnification for surface roughness evaluation using machine vision, *Int J Mach Tools Manuf.* 2005; 45: 228–34p.
24. Allebach J., Wong P.W. *Edge-Directed Interpolation, School of Electrical and Computer Engineering.* Purdue University, West Lajayette, IN 47907-1285, work done at Hewlett Packett, CA.
25. Majumdar A., Bhushan B., Role of fractal geometry in roughness characterization and contact mechanics of surfaces, *ASME J Tribol.* 1990; 112: 205–16p.

Biography

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