

ASSESSMENT OF SURFACE ROUGHNESS OF MOVING SURFACES

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Abstract: Computer vision with digital image processing is one of the widely used research tools and finds many applications in various branches of engineering. In a manufacturing environment, it is used for many applications such as inspection, recognition and navigation. In this work, the objective is to evaluate the surface roughness of uniformly moving machined surface using machine vision technique. Basically, the problem in estimating the roughness of moving surfaces based on their images is blurring. It is important that blurred image has to be corrected for its distortion and restored before any further analysis. This image restoration needs to be resolved before proceeding to the evaluation of roughness of such surfaces. In this work, geometric distortion removal technique is used for image restoration. Then, the quantification of surface roughness using these improved quality images is carried out using various parameters such as spatial frequency, arithmetic mean value and standard deviation. Group method of data handling (GMDH) technique was used to compare the optical roughness parameters calculated using the digital surface images and the widely used mechanical stylus instrument values. An analysis based on the comparison to understand the validity of the present approach of estimation of surface finish based on the digitally processed images for implementation in practice, is presented in this paper.

Key words: Machine vision, Moving objects, Surface roughness.

1. INTRODUCTION

The measurement of roughness on machined surfaces is of great importance for manufacturing industries as the roughness of a surface has a considerable influence on its quality and function of products. The conventional method for measuring surface roughness is to pass a stylus probe across the surface and monitor its movement such that the surface micro profile can be traced. These devices are very sensitive, and the diamond stylus could scratch the surface particularly when the materials are soft. A common drawback of this approach is the small area using which the roughness is evaluated at any one time and also the transducer is very sensitive and the stylus tip is fragile. Therefore, the instrument must be handled carefully in a fairly, clean environment. Another problem with the stylus measurement technique is the size of the stylus radius and the crevices of the surface. If the crevices are narrow such that the stylus cannot penetrate all the way to the bottom, the measurement will not be accurate. Considering these drawbacks the need and the importance for non-contact techniques for measurement of surface roughness becomes apparent.

Extensive research has been performed by many earlier researchers (Luk, 1989; Damodaraswamy, 1991; Al-kind, 1992) on machine vision approaches which have the advantages such as non-contact, faster than contact methods and are capable of measuring an area of the surface rather than a single line which makes it a 3-D evaluation. In this work, machine vision is used to image the motion blur, that is, blur that occurs when the motion has constant speed and in a fixed direction. The blurred image is modeled as a convolution between the original

image and a known point spread function. The Richardson-Lucy Restoration algorithm, a method of estimation based on Bayes theorem has been used to correct the image (Richardson, 1972). The Richardson-Lucy algorithm, also known as Richardson-Lucy deconvolution, is an iterative procedure for recovering a latent image that has been blurred by a known point spread function. The noise is assumed to be Gaussian. Once the images are restored using a proven established deblurring algorithm an attempt was made to evaluate the roughness using images of surfaces made using different machining processes such as grinding and milling.

2. MODEL OF THE IMAGE DISTORTION PROCESS

In order to develop an image restoration algorithm, there is a need to develop an image distortion model. Image deblurring helps to correct images which have been blurred by motion, de-focus or by atmospheric turbulence. There are several major groups of image restoration methods. More the specialization of a particular type of correcting method, better the accuracy of the corrected image is. For example, Weiner filters are very useful when the auto correlation or other such data about the noise is available. But when correcting astronomical images, the maximum entropy filter is the best. So, there is a vast scope of specializing algorithms for deblurring objects. Defects in deblurring images occur commonly due to the presence of artifacts. This may be due to wrong assumption that the point spread function is constant across the image. Artifacts also result when the algorithm aims to deblur only one part of the image.

Therefore, it can be seen that the appropriate algorithm to be used depends on the type of blur that needs to be removed. The generalized image distortion problem can be represented (Richardson, 1972) by the following equation

$$g(u, v) = s \left[\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} h(u, v, u_i, v_i) \cdot f(u_i, v_i) du_i, dv_i \right] \odot n(u, v) \quad (1)$$

Here $g(u, v)$ represents the distorted image, $f(u_i, v_i)$ represents the ideal image and $h(u, v, u_i, v_i)$ represents the point spread function (PSF). In this generalized case the PSF may vary with the indices and need not be constant. The noise that affects the image formation at the time of recording is given by $n(u, v)$. The symbol \odot represents a point by point operation. Most recording systems, such as those which use photographic film, introduce a point nonlinearity represented by $s[\cdot]$ shown in Eqn.1.

Some assumptions may be made about the degradation process to simplify this equation. It can be assumed that the point nonlinearity is negligible, the noise introduced to the system is purely additive, and the PSF acts as a linear shift invariant operator on the true image. These assumptions are commonly used in practice for a variety of applications. On applying these assumptions the equation simplifies to:

$$g(u, v) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} h(u - u_i, v - v_i) \cdot f(u_i, v_i) du_i, dv_i + n(u, v) \quad (2)$$

On using discrete values the above integral becomes a summation of the form shown below:

$$g(u, v) = h(u, v) \otimes f(u, v) + n(u, v) \quad (3)$$

Where $g(u, v)$ represents the blurred image, $f(u, v)$ is the ideal image, $h(u, v)$ is the convolution operator and $n(u, v)$ is the additive noise and \otimes is the symbol for convolution. The special case of correcting images of machined surfaces in order to evaluate the surface roughness is a particularly challenging task. Typically, surface images are homogenous in all directions and have small variations from the mean pixel value of the image. These small deviations from the mean are easily lost when the image is blurred. Most deconvolution methods fail to correct surface images because of this very reason. The correction can be done effectively if the spatial/spectral characteristics of the input PSF are very well known (from observations or from simulations). This work explores the possibility of using such an approach for correction of moving images of the machined surfaces.

3. PROBLEM DEFINITION AND ASSUMPTIONS

The problem considered here is the restoration of images blurred by uniform motion blurring. The system

has been assumed to be Linear Shift Invariant (LSI). This assumption can be justified given the small field of view being used and the type of blurring involved. Since uniform motion blur is considered, the blurring is dependant on the speed of motion of the object. Since all parts of the image are moving at the same speed, it is admissible to assume that all are degraded by the same amount of blur. The second assumption is that the noise introduced in the image is Gaussian and additive. Zero mean Gaussian noise of varying variance is considered for the algorithm. The problem addressed by this work can be stated as:

“Given a gray-scale image $g(x, y)$ degraded by a linear shift invariant PSF $h(x, y)$, find a reliable estimate of the true image $f(x, y)$ given information about the PSF and partial knowledge of the true image.”

4. PROPOSED APPROACH

This work approaches the problem of deblurring by using the Richardson-Lucy (RL) algorithm (Richardson, 1972; Lucy, 1974; Biggs, 1997). It attempts to maximize the likelihood of the restored image by using the expectation maximization algorithm (Vardi, 1982). The algorithm requires a good estimate of the process by which the image is degraded for accurate restoration. The degradation can be caused in many ways, such as subject movement, out of focus lenses or atmospheric turbulence, and is described by the point spread function (PSF) of the system. Starting with a guess for the original image, the Lucy-Richardson algorithm updates its guess on each iteration so it tends toward the latent image. In theory, the longer the algorithm is iterated, the closer it comes to converging to the latent image. The RL iteration can be derived from the imaging equation and the equation for Poisson statistics

$$I(i) = \sum_j p(i|j) O(j) \quad (4)$$

Where O is the unblurred object, $p(i|j)$ is the PSF (the fraction of light coming from true location j that gets scattered into observed pixel (i) and $I(i)$ is the noiseless blurry image. The joint likelihood \mathcal{L} of getting the observed counts $D(i)$ in each pixel given the expected counts $I(i)$ is

$$\ln \mathcal{L} = \sum_i D(i) \ln I(i) - I(i) - \ln D(i) \quad (5)$$

The maximum likelihood solution occurs where all partial derivatives of \mathcal{L} with respect to $O(j)$ is zero

$$\frac{\partial \ln \mathcal{L}}{\partial O(j)} = 0 = \sum_i \left[\frac{D(i)}{I(i)} - 1 \right] P(i|j) \quad (6)$$

The iterative RL iteration algorithm may be succinctly expressed as

$$O_{new}(j) = O(j) \sum_i P(i|j) \frac{D(i)}{I(i)} / \sum_i P(i|j) \quad (7)$$

It is clear from a comparison of Eqns. (6) and (7) that if the RL iteration converges (as has been proven by Vardi, 1982), meaning that the correction factor approaches unity as the iterations proceed, then it must indeed converge to the maximum likelihood solution for poisson statistics in the data.

5. CAPTURING IMAGES OF MOVING MACHINED SURFACES

The experimental setup is a combination of linear stage and a vision system, the schematic diagram and experimental set up is shown in Fig.1. Specimens are made of different roughness using manufacturing processes viz., grinding and milling and were kept on a motor-driven linear stage. A stepper motor controller is used to vary the linear speed of the linear stage. The image of the surface, which is moving at a constant speed of 25.4 mm per second, is grabbed by a vision system, which is a combination of a video zoom microscope and a monochrome CCD sensor. The magnification of the imaging system is 2X. The optical axis of the system is perpendicular to the nominal plane of the test surface. Image sequences are captured through a frame.

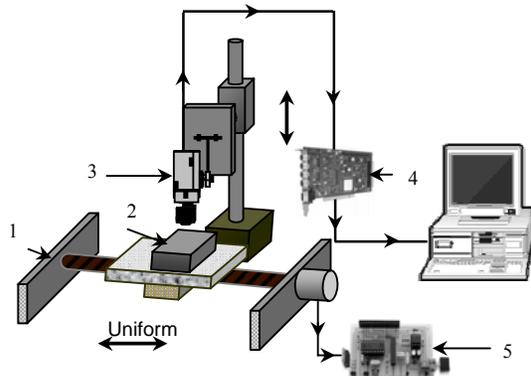


Fig. 1 Schematic arrangement for capturing moving machined surface.

1. Linear stage
2. Specimen
3. CCD camera
4. Matrox frame grabber card
5. Stepper motor controller.

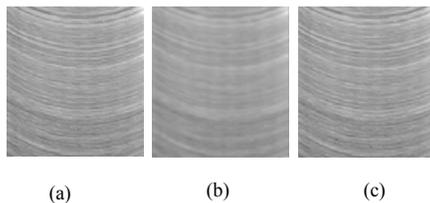


Fig.2 Results of Richardson-Lucy iterative technique for a Milled surface ($R_a=0.649\mu\text{m}$) (a) Original image

(b) Blurred image (PSNR=21.132 db) (c) Restored image after 100th iteration (PSNR =27.655 db).

grabber into a computer in real time for further analysis. Illumination of the specimens was accomplished by a diffuse, white light source which was situated at an angle of approximately 45° with respect to the specimen surface.

6. GMDH FOR SURFACE ROUGHNESS ASSESSMENT BASED ON RESTORED MACHINED SURFACE IMAGES

In this study, after restoration the images of machined (grinding and milling) surfaces, the statistical roughness parameters of image texture (spatial frequency (SF), arithmetic mean value (Ga) and standard deviation (STD)) are calculated.

Spatial frequency (SF)

$$F = u_1^2 + v_1^2 \quad (8)$$

where u_1, v_1 are the frequency coordinates of the maximum peak of the power spectrum. The image surface roughness parameter (SF) is calculated from the power spectrum of the surface image. The 3-D perspective of the corresponding power spectrum after deblurring for milled surface is shown in Fig.3.

Standard deviation of gray level (STD)

The fluctuation is the natural property of surface roughness consisting of high, medium and low frequency variations. The parameter standard deviation represents the overall variation with respect to the mean.

The arithmetic average of the gray level (Ga)

$$Ga = \sqrt{\sum (F_{m,n} - F_{i,j})^2 / (8F_{av})} \quad (9)$$

Where: $(m,n) = (i, j-1), (i,j+1), (i+1,j), (i+1,j-1),$

$(i+1,j+1) (i-1,j), (i-1,j-1)$ and $(i-1,j+1)$

$$F_{av} = \sum F_{m,n} / 8$$

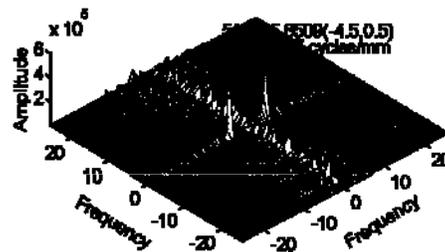


Fig. 3 Power spectra in 3-D perspective for surface images after image restoration for a milled surface ($R_a = 0.325 \mu\text{m}$).

In this paper, the group method of data handling (GMDH) is used to predict the vision roughness parameter (R_v) using parameters calculated from the images namely major peak frequency, principal component magnitude squared value, and standard deviation. Then, this predicted/estimated value is compared with that of the surface roughness obtained using a stylus instrument (R_a) for machined surfaces before and applying SR reconstruction algorithm and are presented in Table1. The GMDH is an established technique for obtaining the polynomial description of a stochastic system from a small amount of experimental data. The GMDH procedure (Ivakhenko AG, 1971; Farlow 1984) uses partial description in the form of second order polynomials with

$$y_k = b_0 + b_1X_i + b_2X_j + b_3X_i^2 + b_4X_j^2 + b_5X_iX_j \quad (10)$$

where y_k denotes an intermediate variable and X_i, X_j are a pair-wise combination of normalized input variables and b_0, b_1, \dots, b_5 are the coefficients.

7. RESULTS AND DISCUSSION

Based on the Richardson-Lucy (RL) algorithm, the blurred images of machined surfaces have been restored, and then the image roughness parameters are estimated. Restoration results using RL algorithm for a machined surface (milling) is shown in Fig. 2. The RL algorithm has been successful in recovering high spatial frequency information and is very powerful on the basis of its resolving power.

Once the images are restored using deblurring algorithm, an attempt was made to evaluate the vision roughness (R_v) of milled and ground surfaces using the corrected images and also the prediction of roughness was done using GMDH algorithm. It was found that the deblurring algorithm worked well for relatively rough surfaces. In such surfaces, lay pattern is predominant and the blur caused by uniform motion was clearly visible and the deblurring algorithm was more effective. As the surface (ground) becomes finer, it becomes difficult to identify motion blur and the effectiveness of the restoration algorithm decreases as the effect of edge detection on such fine images had less influence. It was found that the vision roughness parameters had a good correlation (Fig.4) with the roughness values obtained by the stylus based method for a rough milled surface.

8. CONCLUSION

The removal of blur in the images of moving surfaces has been successfully implemented in this work. Then the improved images have been used for evaluation of vision roughness (i.e. roughness estimation using digital images captured using a vision system). There is a very good correlation between the vision roughness and the stylus roughness, this is particularly true for milled surfaces.

Table.1 Comparison of statistical texture parameters (Milling) and stylus instrument values for testing dataset

Data No	Roughness parameter calculated from image texture			Roughness values	
	SF	Ga	STD	Vision (R_v)	Stylus (R_a)
	(cycles/mm)	(gray level)	(gray level)	(μm)	(μm)
1	4.53	0.10	48.46	0.80	0.78
2	5.02	0.11	47.93	0.82	0.89
3	5.02	0.11	48.86	0.88	0.91
4	14.51	0.11	47.75	1.93	1.92
5	4.53	0.11	48.81	0.58	0.69
6	7.52	0.12	45.62	0.71	0.71
7	5.02	0.10	47.46	0.74	0.78
8	7.07	0.11	45.64	0.69	0.71
9	5.02	0.11	39.94	0.48	0.37
10	5.52	0.11	45.46	0.48	0.40
11	5.02	0.10	44.58	0.38	0.42
12	4.61	0.11	43.86	0.29	0.17
13	19.60	0.12	46.38	0.75	0.76
14	9.01	0.11	40.60	0.13	0.19
15	5.02	0.11	42.90	0.32	0.16
16	4.53	0.10	42.77	0.32	0.31
17	4.53	0.11	42.52	0.30	0.34
18	16.07	0.11	44.37	0.13	0.17
19	5.02	0.11	42.60	0.32	0.38
20	4.53	0.10	43.80	0.30	0.33
21	4.53	0.10	43.11	0.31	0.37
22	17.61	0.11	45.15	0.19	0.23
23	4.61	0.11	48.69	0.50	0.38
24	8.02	0.10	42.99	0.32	0.45
25	7.52	0.10	43.61	0.41	0.42
26	4.53	0.10	46.01	0.43	0.30
27	13.76	0.10	45.44	0.65	0.65

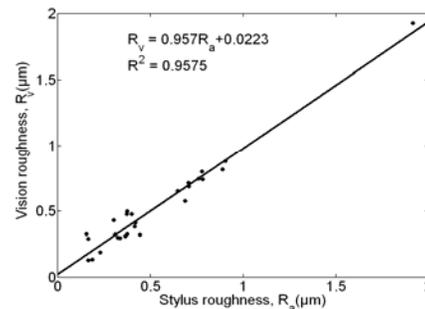


Fig. 4 Correlation between roughness obtained from vision and stylus based methods for milled surfaces.

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