ROUGHNESS ESTIMATION OF INCLINED SURFACES USING ARTIFICIAL INTELLIGENCE

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Abstract: Practical use of Machine Vision for surface roughness estimation faces many challenges, as in this case only image is used for evaluation and not the component. In such cases, if the component is kept at an angle during imaging, there is a possibility of getting distorted information and therefore the consistency of evaluation/ quantification would become a problem. So, there is a need to ensure that the measured surface is kept horizontal and flat when the image is being taken. In this work, estimation of the surface roughness has been done and analysed using digital images of machined surfaces obtained by a Machine Vision system deliberately maintained at varying angles. The quantitative measures of surface roughness are extracted in the spatial frequency domain using a two dimensional Fourier Transform. An artificial neural network (ANN) is trained and tested to arrive at the Ra values using the input obtained from the digital images of inclined surfaces which include optical roughness parameters estimated and angular of inclination of test parts. The estimated optical roughness parameter results based on the images of the surfaces are compared with the surfaces that are kept horizontal and the results are presented and analysed in this paper. In addition optimal combination of calculated roughness parameters which act as input to the ANN in order to obtain best correlation between estimated R_a using ANN and stylus measured R_a value is determined.

Keywords: Machine vision; Artificial neural networks; Surface roughness;

1. INTRODUCTION

The quality of components produced is of main concern to the manufacturing industry, which normally refers to dimensional accuracy, form and surface finish. Therefore, the inspection of surface roughness of the work piece is very important to assess the quality of a component, which is normally performed using stylus type devices, which correlate the vertical displacement of a diamond – tipped stylus to the roughness of the surface under investigation. This process is accurate, accepted widely by all the users. But, this method is not suitable for high volume applications as it is time consuming and cumbersome. Another disadvantage of this stylus method is that it requires direct physical contact with the component and the resolution of this instrument depends mainly on the diameter of the measuring probe tip.

With growing demand of industrial automation in manufacturing, machine vision plays an important role in quality inspection and process monitoring. Machine vision for industry has generated a great deal of interest in the technical community over the past several years. Extensive research has been performed on machine vision applications in manufacturing, because it has the advantage of being non-contact and as well faster than the contact methods. Using Machine Vision, it is possible to evaluate and analyse the area of the surface, which makes it a 3D evaluation [1, 2, 3]. Machine vision is many times considered as a subset of artificial intelligence. Machine vision typically employs a camera, a frame grabber, a digitiser and a processor for inspection tasks where precision, repetition (particularly for mass produced components) and/or high speed are needed.

Over the years, the non-contact optical methods have attracted researchers' attention for the assessment of surface roughness. Most of the methods are based on statistical analysis of grey-level images in the spatial domain. The intensity histograms of the surface images have been utilized to characterize surface roughness and quality. 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 machined surfaces [4]. Hoy and Yu proposed the two-dimensional Fast Fourier Transform of the digitised surface image in which the magnitude and frequency information obtained from the FFT are used as measurement parameters of the surface finish [5].

All these methods use the basic assumption that the surface of the specimen is completely flat and there is no inclination when the images are captured. Even a small inclination of the specimen may result in inconsistent estimation of roughness of components using machine vision primarily due to the fact that illumination, shadow on the images is likely to be different.

In this work, the machined surfaces are deliberately kept inclined at various angles to the horizontal and their images were captured using a Machine vision system. Then the surface roughness parameters in the spatial frequency domain are estimated and are then used as input to the ANN. The output of the ANN i.e. calculated R_a varies with the number of input and the surface roughness parameters. Hence, selection of optimum combination of input data is of practical importance while estimating surface roughness using ANN.

2. EXPERIMENTAL PROCEDURE

The schematic diagram of the Machine vision system is shown in Fig. 1. The basic experimental set-up consists of a vision system (CCD camera: Pulnix -TM6, 768 x 565 pixels, with Image, LC processing hardware with 4 frame buffers and 1/30 s grabbing speed) and an appropriate lighting arrangement. Illumination of the specimens was accomplished using a diffused white light source, which is kept at an angle of approximately 45° incidence with respect to the specimen surface as shown in Fig. 1.

The experiments were carried out using flat mild steel specimens manufactured by grinding process. Surfaces with varying roughness / textures were obtained by controlling the machining parameters. The specimens were first placed on a flat surface and the images were taken. Images of the surface were then taken at varying angles (0°-12°) so as to analyse the surface roughness parameters estimated for small changes in angles that may inadvertently occur during normal use of the machine vision approach. Surface images were grabbed by the CCD camera and were pre-processed to eliminate illumination and noise effects.

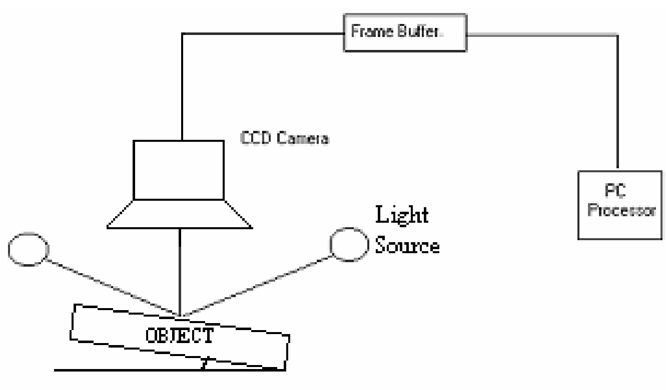

Fig.1. Schematic diagram of the Machine Vision system.

3. ESTIMATION OF SURFACE ROUGHNESS PARAMETERS

The most important requirement in roughness assessment using machine vision is to extract the roughness parameters of surfaces using images. In this work, surface roughness parameters are extracted based on spatial frequency domain using the 2D Fourier transform. The Fourier transform characterises the surface images in terms of frequency components [6].

This work is confined to roughness assessment of ground surfaces inclined at varying angle to the horizontal plane. Liu and Jernigan have derived a set of 28 texture features in the spatial frequency domain [7]. In this study, five roughness features were chosen from them and are used. They are given below.

Let, $$p(u,v) = \frac{P(u,v)}{\sum_{(u,v)\neq(0,0)} P(u,v)}$$

be the normalized power spectrum, which has the characteristics of a probability distribution. Where P (u,v) is the power spectrum of the image I(x,y).

3.1. Major Peak Frequency F_1

$$F_1 = (u_1{}^2 + v_1{}^2)^{1/2}$$

Where (u_1, v_1) are the frequency coordinates of the maximum peak of the power spectrum i.e,

$$p(u_1, v_1) = \max[\, p(u,v) \forall (u,v) \neq (0,0)]$$

Feature F_1 is the distance of the major peak (u_1, v_1) from the origin (0, 0) in the frequency plane.

3.2. Principal component Magnitude Squared, F_2

$$F_2 = \lambda_1$$

Where λ_1 is the maximum Eigen value of the covariance matrix of p(u,v). The covariance matrix M is given by

$$M = \begin{bmatrix} Var(u^2) & Var(uv) \\ Var(vu) & Var(v^2) \end{bmatrix}$$

For which

$$Var(u^2) = \sum_{(u,v)\neq(0,0)} u^2 . p(u,v)$$

$$Var(v^2) = \sum_{(u,v)\neq(0,0)} v^2 . p(u,v)$$

$$Var(uv) = Var(vu) = \sum_{(u,v)\neq(0,0)} uv . p(u,v)$$

Feature F_2 indicates the variance of components along the principal axis in the frequency plane.

3.3. Average power spectrum F_3

$$F_3 = \sum_{(u,v)\neq(0,0)} P(u,v) / S$$

Where $S=N^2-1$ for a surface image of size N × N

3.4. Central Power Spectrum Percentage, F_4

$$F_4 = \frac{P(0,0)}{\sum_u \sum_v P(u,v)} \times 100\%$$

The frequency component at the origin (the centre) of the frequency plane has the maximum power spectrum.

3.5. Ratio of Major Axis to Minor Axis F_5

$$F_5 = (\lambda_1 / \lambda_2)^{1/2}$$

Where λ_1 and λ_2 are the maximum and minimum eigen values of the covariance matrix of P(u,v).

4. NEURAL NETWORKS FOR SURFACE ROUGHNESS ASSESSMENT

After estimating the roughness features F_1, F_2, F_3, F_4 and F_5 using the images, an attempt is made in this work by using them as input to predict the roughness value Ra using Artificial Neural Networks (ANN). ANNs are computing systems made up of a number of simple, highly interconnected processing elements called neurons, which processes information by their dynamic state response to external inputs. A neuron is a simple processor, which takes one or more inputs and produces an output. Each input into the neuron has an associated weight that determines the ''intensity'' of the input. The processes that a neuron performs are: multiplication of each of the inputs by its respective weight, adding up the resulting numbers for all the inputs and determination of the output according to the result of this summation and an activation function. While a single neuron is of very limited use, a number of connected neurons, i.e. a network, can be trained to perform certain tasks. Data is fed into the network through an input layer, it is processed through one or more intermediate hidden layers and finally it is fed out of the network through an output layer, Fig. 2 [8].

The training process involves presenting a set of input patterns with known outputs to the ANN. The system adjusts the weights of the internal connections to minimise errors between the network output and target output. After the ANN is satisfactorily trained, it will be able to respond to unseen input data to predict required output, within the domain covered by the training examples [9].

Back-propagation neural network used for estimating the surface roughness of the machined surfaces with varying angles of inclination. The input to the network is a subset of calculated roughness parameters and angle of inclination. The structure of an ANN is shown in Fig. 2. In the training phase, the desired value of the node in the output layer is the actual roughness value R_a calculated by stylus method. In the testing phase of the neural network, the estimated roughness, R_a is given by the value of the node in the output layer.

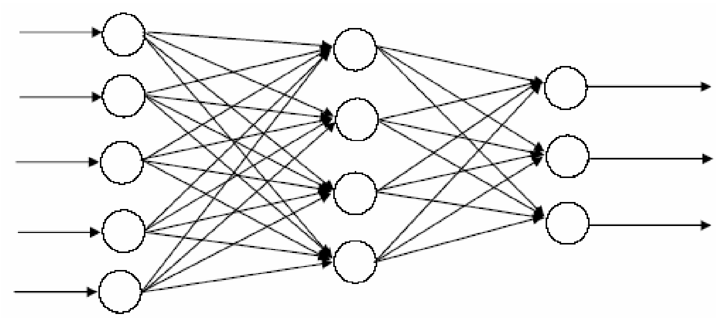

Fig.2. Typical Artificial Neural Network

5. EXPERIMENTAL RESULTS

In this section experimental results are presented for evaluating the validity of the proposed quantification of optical roughness parameters and the performance of the neural networks for roughness assessment for different combination of roughness parameters. Roughness parameters F_1, F_2, F_3, F_4 and F_5 are calculated for test specimens deliberately kept at different angles of inclination θ. It is observed that the values of roughness parameters calculated based on such inclined images vary with the angle of inclination of the surfaces.

Roughness parameters are then calculated for 9 test specimens at different angle of inclination (0°-12°). The input and output data are separated into training and testing sets. ANN are however, only able to process the data in a certain format. Therefore normalization of data is done before presenting the training patterns to the network. Normalization function is represented by the following relationship:

$$A = (V / 10^n)^{1/2} + C$$

C is a constant, usually between -0.25 and 0.25 to ensure that the values are in the range of 0.2 to 0.8. 'n' is the number of digits in the integer part of the variable V [9].

With nine test samples and twelve varying angles of inclinations, 117 combinations are possible and all of them have been used for estimation. Out of 117 images 94 are used for training the ANN and remaining 23 are used for testing the ANN. The selection of testing and training data is based on the work done by earlier researchers [9].

The optimal subset of the roughness parameters for ANN is then determined by evaluating all possible combination of roughness parameters. The best combination of roughness parameters is determined based on minimum R.M.S roughness error, which is calculated using the following equation.

$$R.M.S.Roughness\ Error = \left[\sum_j \left(R_j^* - R_j \right)^2 / N \right]^{1/2}$$

Where R_j^* is the actual roughness value or stylus R_a value and R_j is the estimated roughness value from the ANN for the j^{th} sample in the test set. N is the total number of samples in the test set.

The calculated roughness parameters (F_1, F_2, F_3, F_4 and F_5) and angle of inclination of the component (θ) are used as input to the ANN. The ANN is tested by varying the number and combinations of inputs as shown in table 1, 2 and 3. When two roughness parameters and angle of inclination are used as input to the ANN, the combination of F_1 and F_4 yields minimum R.M.S roughness error of 0.048 and maximum correlation of 84.7% between stylus R_a and ANN R_a. For three selected parameters, combination of F_1, F_3 and F_4 yields minimum R.M.S roughness error. In case of four parameters, R.M.S roughness error is least when F_1, F_2, F_3 and F_4 are given as input to the ANN. The over all minimum R.M.S roughness error of 0.041 is obtained by the combination of all the five roughness parameters, F_1, F_2, F_3, F_4 and F_5. It is also seen from table 3 that absence of F_1, ie, major peak frequency results in considerable increase in the R.M.S. roughness error. Therefore major peak frequency, F_1 is a very effective and reliable feature for estimating the roughness value.

Table 1. R.M.S roughness error and percentage correlation of calculated R_a and Stylus R_a for the possible combination of two roughness parameters

Possible Combinations of inputs	R.M.S Roughness error	Percentage Correlation between stylus R_a and ANN R_a (%)
F_1, F_2, θ	0.07032	74.7
F_1, F_3, θ	0.07028	67.0
F_1, F_4, θ	**0.04804**	**84.7**
F_1, F_5, θ	0.08101	74.6
F_2, F_3, θ	0.05663	84.7
F_2, F_5, θ	0.05692	82.5
F_3, F_4, θ	0.06835	72.8
F_3, F_4, θ	0.01151	23.9
F_3, F_5, θ	0.09326	34.0
F_4, F_5, θ	0.08514	30.8

Table 2. R.M.S roughness error and percentage correlation of calculated R_a and stylus R_a for the possible combination of three roughness parameters

Possible Combinations of inputs	R.M.S Roughness error	Percentage Correlation between stylus R_a and ANN R_a (%)
F_1, F_2, F_3, θ	0.05069	80.8
F_1, F_3, F_4, θ	**0.04818**	**84.5**
F_1, F_3, F_5, θ	0.07939	56.9
F_1, F_2, F_4, θ	0.05794	81.4
F_1, F_2, F_5, θ	0.05806	77.7
F_1, F_4, F_5, θ	0.05931	84.5
F_1, F_4, F_5, θ	0.04667	83.8
F_2, F_3, F_4, θ	0.05907	78.6
F_3, F_4, F_5, θ	0.10787	31.1
F_2, F_3, F_5, θ	0.05553	82.3

Table 3. R.M.S roughness error and percentage correlation of calculated R_a and stylus R_a for the possible combination of four roughness parameters

Possible Combinations of four parameters	R.M.S Roughness error	Percentage Correlation between stylus R_a and ANN R_a (%)
F_1, F_2, F_3, F_4, θ	**0.04602**	**84.3**
F_1, F_3, F_4, F_5, θ	0.05296	81.5
F_1, F_2, F_4, F_5, θ	0.05798	77.4
F_1, F_2, F_3, F_5, θ	0.04888	83.5
F_2, F_3, F_4, F_5, θ	0.07109	55.3

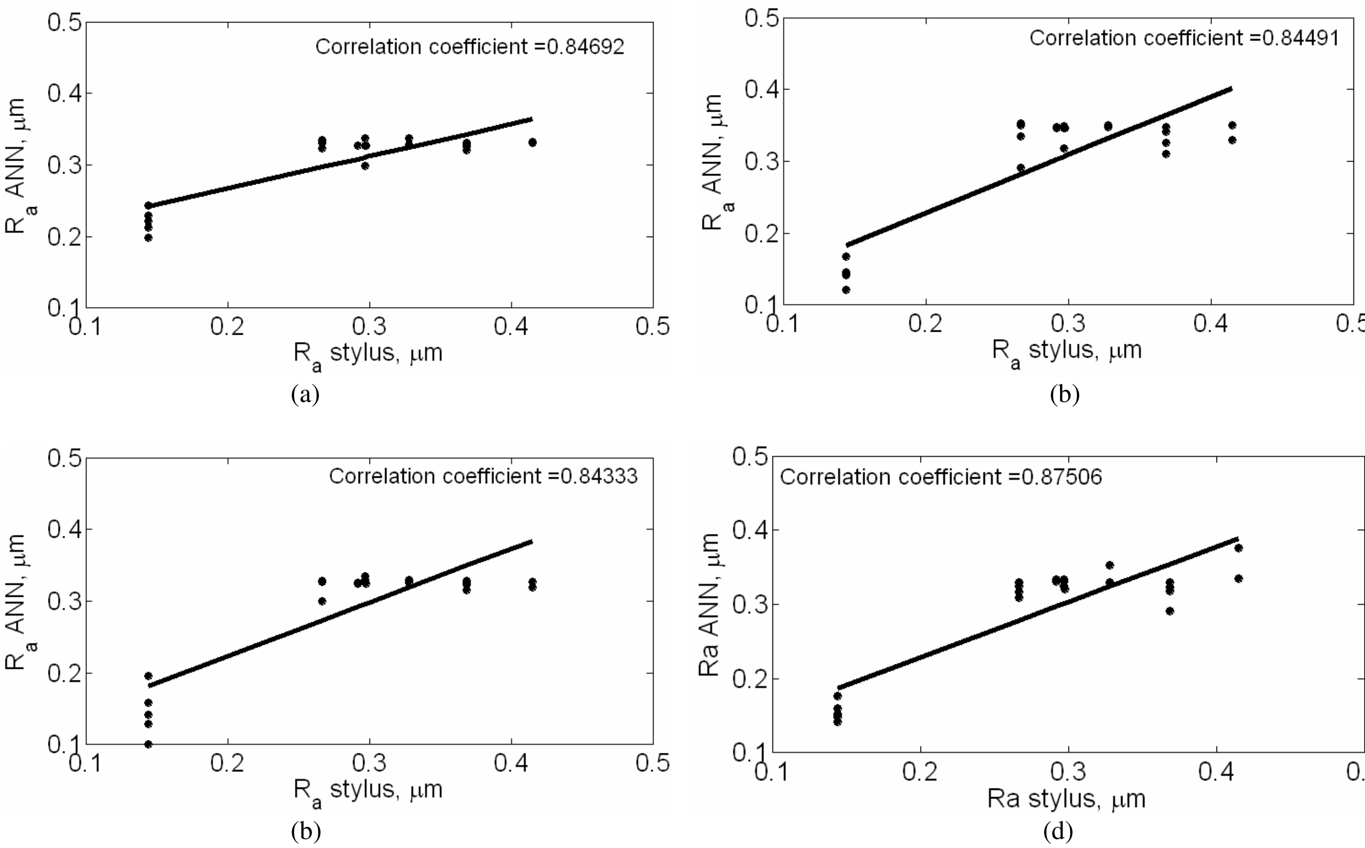

Fig. 3. Graphs showing R_a ANN vs. R_a stylus at various angle of inclination, for different combination of roughness parameters. (a) for input combination F_1, F_4, θ; (b) for input combination F_1, F_3, F_4, θ; (c) for input combination F_1, F_2, F_3, F_4, θ; (d) for input combination F_1, F_2, F_3, F_4, F_5, θ.

It is also observed that the combination of F_1 and F_4 results in better correlation between stylus R_a and ANN R_a and least R.M.S roughness error. Overall maximum R.M.S roughness error of 0.107 is obtained by the input combination of F_3, F_4, F_5 and θ. For two selected roughness parameters, combination of F_3 and F_5 results in higher R.M.S roughness error (table 1). Thus, the presence of roughness parameter, F_5 increases the R.M.S roughness error and results in poor correlation between calculated and measured roughness value. Hence, the selection of appropriate combination of input data affects the desired output to a large extent.

7. CONCLUSION

In this work a non-contact machine vision approach is used for estimating the optical roughness of ground surfaces by keeping them inclined at varying angles to the horizontal. An ANN has been used for predicting the roughness values of the components using the optical roughness parameters obtained from the Fourier transform of the image as input. The ANN is tested with all the possible combinations of roughness parameters by varying the number of inputs and the optimum combination for the surface parameter estimation is arrived at. The predicted roughness values using ANN are found to be correlating well with the conventional stylus R_a values even when the test specimen images are taken at varying angles. The proposed methodology can be applied to the machined parts in a manufacturing environment where it is difficult to ensure absolute flatness during imaging of the surfaces to be tested. Therefore the machine vision and ANN approaches could very well be used for estimation and prediction of roughness of components respectively.

8. REFERENCES

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