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VISION BASED SURFACE ROUGHNESS EVALUATION OF GROUND COMPONENTS USING WAVELET TRANSFORM AND NEURAL NETWORK

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Abstract: This paper describes a non-contact technique to assess the differences in surface characteristics of the ground components. The computer vision based system is used to analyze the pattern of scattered light from the surface to asses the surface roughness of the component. The ground specimens were manufactured using varying machining parameters. The images of the specimens are captured using a CCD camera. The image parameters based on the wavelet transform are evaluated. Then, the evaluated parameters along with the cutting parameters were used to train the artificial neural network to predict the surface roughness parameters R_a , which is measured using the stylus instrument. The comparison of stylus R_a and that predicted using ANN are presented and analyzed in this paper.

Keywords: machine vision, surface roughness, wavelet transform, neural network

1.INTRODUCTION

The surface quality of the components produced in the manufacturing processes should be assessed to control the process and predict the functional performance of the components. Surface finish measurement also useful in providing an index of process stability. In all the manufacturing processes, by using proper machining parameters it is possible to control the quality of the produced components. The manufacturing of accurate parts is dependent upon being able to predict and control the errors that occur in manufacturing machines. Surface analysis relies on the assumption that the surface geometry irregularities can be used as a fingerprint of the process and machine tool [2]. The slightest change in the process parameters or the condition of the machine tool manifest itself as changes in surface geometry, in size, texture, form, or a combination [2]. The traditional method of surface roughness measurement is done using the stylus instrument. The major disadvantage of such an instrument is that require direct physical contact and line samplings, which may not represent the real characteristics of the surface [3].

Light scattering was introduced as a practical tool for Surface roughness measurement. In this, a light beam of a certain wavelength is made incident on the surface under test at a controllable angle of incidence. The measurement of scattered light intensity as a function of scattering angle and surface roughness parameter results into specific quantitative parameters. In addition, light scattering methods are generally used for studies of surface whose root mean square parameter (R_q) is much less than the wavelength of the incident beam. The resolution of such surface roughness measurement was limited by the wavelength of the source. The optical techniques can achieve faster inspection speed, although they donot provide enough information to characterize the surface topography and surface texture which are needed for applications in machining process monitoring. With the advent of high-speed computer with image processing hardware and software made the machine vision technique as a better alternative for measuring the surface roughness of the components. This method uses a machine vision system to capture the image of the surface, which is illuminated properly based on the application. The image is subsequently processed using the wavelet transform to represent the image in space-frequency domain. The proposed measurement system makes use of the statistics of the wavelet coefficient magnitudes to derive the surface roughness parameter.

2. MACHINE VISION BASED SURFACE ROUGHNESS MEASUREMENT

The surface roughness of the component is evaluated from the captured images of its surface. The machine vision based surface roughness measurement was pioneered by the work of Luk et al. [1]. They used the statistics of the histogram of captured surface images of tool steel samples for surface roughness measurement. The image parameters are correlated well with the surface roughness of the components measured using the stylus instrument. There were many researchers investigated the use of machine vision based techniques for assessing the surface roughness as well as classification of machined surfaces. Hoy et al. [11] investigated the use of frequency domain information for the analysis of the surface roughness of the components. Ramamoorthy et al. [3] [4] [12], presented machine vision based image analysis for surface roughness analysis and classification of machined surfaces. Sodhi et al [1996], Younis et al [1998], Du-Ming Tsai et al. [1998], Zhang et al. [1996], Julia et al. [1994], AI-kindi et al. [1992], Cuthbert et al. [1992], Lee et al. [2001], [2002], [2004], [2005], Chang et al. [2005] investigated extensively the use of machine vision based evaluation surface roughness of the components manufactured using different processes. In all these reported works, some image parameters are evaluated and correlated with the surface roughness of the component measured using the stylus instrument. The computed vision parameters for surface roughness evaluation are likely to change with illumination and orientation etc. Hence, there is a need for robust image parameter to relate with the surface roughness of the components manufactured by different machining processes. In this regard, an attempt is made in this paper to use the statistics of the wavelet coefficient magnitudes as image parameters to relate with the roughness values measured using the stylus instrument.

3. EXPERIMENTAL WORK

The grinding experiments were carried out in a precision surface-grinding machine with aluminum oxide grinding wheel (AA60 K5 V8) and mild steel specimens. Experiments were carried 'out for traverse grinding without the application of coolant. 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.After each run, the images of the machined surfaces are captured using the Pulnix-TMC-6 CCD camera with appropriate illumination. The surface roughness values for the components are also measured using the stylus instrument

Table.1.Cutting parameters used in the Experiment

S.no	Speed (rpm)	Feed (mm/min)	Depthofcut (Doc) (µm)
1	1500	13	40
2	1800	15	80
3	2100	17	120

4.WAVELET TRANSFORM

Fourier transform is a familiar signal-processing tool that uses periodic functions for signal representation. Specifically, any signal can be approximated by a combination of infinite sine and cosine functions. In Fourier transforms, the time and spatial location of a specific characteristic cannot be specified. The wavelet is a small wave or pulse, which can be compressed and stretched to different scales. The wavelet transform is an effective tool to split a signal into a collection of multistage representations [15][19]. The basic wavelet function is defined as shown equation (1), which is generated by dilation the function using the scaling parameter a and translating the function using the location parameter b

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

For continuous signal x (t), the continuous wavelet transform (CWT) is given by equation (2). Based on the continuous wavelet transform, the discrete wavelet transform (DWT) is constructed by choosing discrete values for a and b. In general, for the DWT, the wavelet dilation and translation is controlled by integer indices m and n, respectively. The basic wavelet function and the DWT of the x (t) will then be given by equations (3) and (4), respectively.

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (2)$$

$$\Psi_{(m,n)}(t) = \frac{1}{\sqrt{a_0{}^m}}\psi\left(\frac{t-nb_0a_0{}^m}{a_0{}^m}\right) \qquad (3)$$

$$W_{m.n} = \int_{-\alpha}^{\alpha} \frac{1}{a_0{}^{\frac{m}{2}}}\psi\left(a_0{}^{-m}t - nb_0\right)x(t)\,dt \qquad (4)$$

The values of $W_{m.n}$ are the coefficients.

For the orthogonal wavelets, the scaling function Φ (t) is defined in equation (5).

$$\phi_{m,n}(t) = 2^{-\frac{m}{2}}\phi\left(2^{-m}t - n\right) \qquad (5)$$

For the 2-D analysis of signals f (t_1,t_2), where t_1 and t_2 are two spatial coordinates, a 2-D DWT bases constructed by using three wavelet functions defined as

$$\psi^H(t_1,t_2) = \phi(t_1)\psi(t_2) \qquad (6)$$

$$\psi^V(t_1,t_2) = \phi(t_1)\psi(t_2) \qquad (7)$$

$$\psi^D(t_1,t_2) = \phi(t_1)\psi(t_2) \qquad (8)$$

where H, V and D represent horizontal, vertical and diagonal functions respectively. The scaling function for the 2-D DWT is given by the equation (9)

$$\phi(t_1, t_2) = \phi(t_1)\phi(t_2) \qquad (9)$$

The separation into different scales using the wavelet and the scaling function is known as the multiscale analysis. Multiscale makes it possible to decompose the signal into different component parts at different scales. There are many different wavelet functions, but each has its own properties. For surface analysis the orthogonal Daubechies 20 wavelet is used to perform the 2D- DWT.

The image containing original surface information can be decomposed, extracted and reconstructed into multiscale representations. The wavelets are used to decompose the captured images of the workpieces into different scales. Then, statistics of the wavelet coefficient magnitudes at different scales are used to predict the surface roughness of the component. Since the wavelet, coefficients are shift variant. The statistics of the wavelet coefficient magnitudes are defined as follows

$$Variance = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j}^{N} I(i,j)^2 \qquad (10)$$

$$Skewness = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j}^{N} I(i,j)^3 \qquad (11)$$

$$Kurtosis = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j}^{N} I(i,j)^4 \qquad (12)$$

where I(i,j) denotes an element of the wavelet packet coefficient matrix at level five, and M and N represent the vertical and horizontal size of the matrix I. To reduce the effect of non-uniform illumination on the evaluated image parameters, the sample mean is removed before the calculation of image texture features [19]. In selecting the prominent detail channels, the channels that are dominant in the decomposed level is chosen for further analysis. Channel D_{5hl} is found to be dominant in all cases. The estimated values are shown in table.2

Table.2.The calculated texture parameters for the surface images

s.no	Variance	Skewness	Kurtosis	Ra (µm)
1	1.264	1.805	6.377	.345
2	0.725	1.641	1.678	.438
3	3.924	1.700	52.314	.320
4	4.683	1.814	86.837	.455
5	1.007	1.561	2.884	.572
6	0.679	1.663	1.553	.343
7	1.086	1.780	4.920	.445
8	1.821	1.900	15.127	.382
9	3.686	1.673	45.074	.384
10	2.362	1.862	24.427	.470
11	5.234	1.884	135.55	.614
12	2.106	1.723	16.162	1.454
13	1.4	1.586	5.776	3.916
14	1.504	1.636	7.071	3.885
15	1.626	1.512	6.876	4.723
16	1.301	1.816	7.097	3.440
17	2.071	1.747	16.094	3.406
18	1.082	1.720	4.283	3.796
19	3.252	1.670	36.010	4.081
20	1.477	1.726	8.187	3.1071

5.NEURAL NETWORK

A neural network is just a set of nonlinear equations that predict an output variable (Y) from input variables *(Xj)* in a flexible way using layers of linear regressions and S-shaped function. A back propagation neural network model is the most widely used in a broad range of application areas. The back propagation neural networks are usually layered, with each layer fully connected to the layers below and above. When the network is given an input, the updating of activation of values propagates forward from the input layer of the processing units, through each internal layer to the output layer of the processing units. Then, the output units provide the network's response. When the network corrects its internal parameters, the correction mechanism starts with the output units and back propagates through each internal layer to the input. The back propagation algorithm involves a forward propagating step followed by a backpropagation. Both the forward and the backpropagation steps are carried out for each pattern presentation during training. In each successive layer, every processing unit sums its inputs and then applies, in general sigmoid function to compute its output. The output layer of units then produces the output of the network. The mathematical formulation of the back propagation referred from [23].

The input vectors for the neural network obtained from the texture analysis of the work piece surface images. The statistics of the wavelet coefficient magnitudes like variance, skewness and kurtosis along with the cutting parameters used as input to the neural network. The output of the neural network is the R_a value of the component. A computer program in matlab for a back propagation neural network has been developed to recognize the input vectors relevant to each surface image and interpret the output.

In the present work, training is done using 20 sets of input data given in the table.2. The input layer in the present network consists of six neurons representing the cutting parameters (speed, feed and depth of cut) along with variance, skewness and kurtosis' of the detail wavelet coefficient magnitudes at level five. The output layer consists of one neuron representing R_a value of the component. All the inputs and outputs are normalized. Mean squared error of 0.0000001 is taken as the desired goal and the network is trained until desired accuracy of error is reached. After the completion of training, the weights are stored along with the network architecture for further use. Finally, the performance *of* neural network is simulated for a new set of data and predicted output of the neural network corresponding actual output shown in table.2.

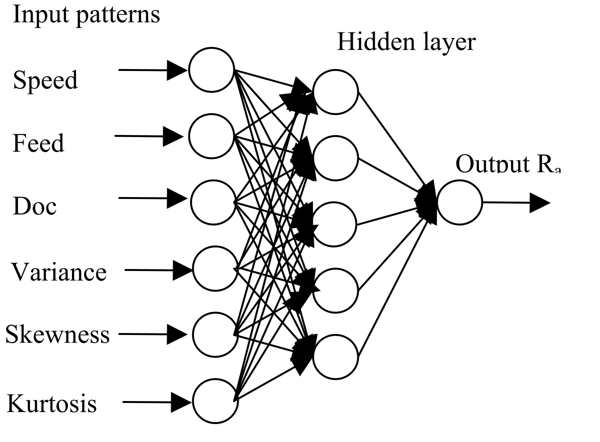

Fig.1 Schematic diagram of BPN neural network used for prediction of Ra

6. RESULTS AND DISCUSSION

To verify the developed neural networks for predicting the surface roughness values, 7 more ground specimens were made using different combinations of machining parameters. The calculated texture image parameters are for the testing data set is tabulated in Table.3. The variance, skewness and kurtosis of the wavelet detailed coefficient magnitudes at level five are calculated. These values are fed to the trained neural network and the surface roughness (R_a) predicted by the neural network. The better correlation between the measured Ra value and predicted R_a value of neural network shows that the method can be used for prediction of surface roughness to control and monitor the surface grinding process.

Table3.Texture parameters and the surface roughness values for verification Tests.

S.no	Variance	Skewness	Kurtosis	Stylus R_a (µm)	Vision R_a (µm)
1	1.097	1.562	3.414	0.3533	0.2861
2	1.187	1.610	4.273	0.4683	0.5445
3	1.008	1.528	2.707	0.4201	0.4201
4	2.469	1.830	24.296	0.3517	0.3183
5	3.168	1.576	28.177	0.3905	0.3906
6	1 .482	1.740	8.304	0.3183	0.2998
7	1.032	1.694	3.686	0.3754	0.3754

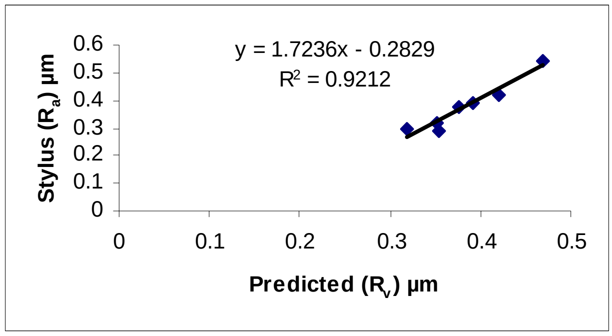

Fig.2.The correlation between the stylus R_a and the predicted R_a by ANN

7.CONCLUSION

In this work, a method is proposed for establishing a relationship between the actual roughness and estimated based on the texture features of the surface image using the neural network. The texture features are evaluated using the wavelet, transform. The variance, skewness, kurtosis are the texture image features evaluated from the detailed wavelet coefficient magnitudes at level five. The texture image parameters along with the machining parameters are used to predict the surface roughness of the ground component. The predicted results of surface roughness were found to be in excellent agreement with the stylus R_a values is shown in Fig.2. Therefore, the proposed method can be effectively implemented using ANN to assess roughness of machined components and monitor the grinding process.

8.REFERENCES

[1] F.Luk, V.Huynh, W.North, "Measurement of surface roughness by a machine vision system", Journal of Physics E.Scientific instruments", Vo1.22, pp.977-980, 1989.

[2] D.J. Whitehouse, "Review Article- Surface metrology", Measurement science and technology, Vo1.8, pp.955-972, 1997.

[3] Ramana.K.V, Ramamoorthy.B, " Statistical methods to compare the texture parameter of machined surfaces", Pattern Recognition, Vo1.29, pp.1447-1459, 1996.

[4] M.B.Kiran, B.Ramamoorthy, V.Radhakrishnan, "Evaluation of surface roughness by machine vision system", International journal of machine tools and manufacture.Vol.38, Nos.5-6, pp.685-690, 1998.

[5] M.A.Younis, "Online roughness measurements using image processing towards an adaptive control", Computers in industrial engineering. Vol.35, Nos 1-2,pp.49-52, 1998.

[6] Du-Ming Tsai, Jeng-Jong Chen, Jeng-Fung chen, "A vision system for surface roughness assessment using neural networks", International journal of advanced manufacturing technology, Vol.14, pp.685-690, 1998.

[7] Manbir S.Sodhi, Khalil Tiliouine, "Surface roughness monitoring using computer vision", International journal of machine tools and manufacture.VoI.36, Nos.7, pp.817-828, 1996.

[8] Guangming zhang, Shivakumar Gopalakrishnan, "Fractal geometry applied to online monitoring of surface finish", International journal of machine tools and manufacture Vol. 36, No.10, pp.1137-1150, 1996.

[9] K.l.Jolic, C.R.Nagarajah, W.Thompson, "Non-contact optically based measurement of surface roughness of ceramics", Measurement science and technology, Vo1.5, pp.671-684, 1994

[10] G.A.AI-kindi, R.M.Baul, K.F.Gill, "An application of machine vision in the automated inspection of engineering surfaces", International journal of production research, Vo1.30, No.2, pp.241-253, 1992.

[11] L.Cuthbert, V.M.Huynh, "Statistical analysis of optical Fourier transform patterns for surface texture assessment", Measurement science and technology, Vol.3, pp.740-745, 1992.

[12] D.E.P.Hoy, F.Yu, "Surface quality assessment using computer vision methods", Journal of material processing technology, Vo1.28, pp.265-274, 1991.

[13]Rajneeshkumar, P.Kulasekar, B.Dhanasekar, B.Ramamoorthy, "Application of digital image magnification for surface roughness evaluation using machine vision", International journal of machine tools and manufacture,voI.35, pp.228-234, 2005.

[14] Kuang-ChyiLee, Shin-Jang Ho, Shinn-Ying Ho, "Accurate estimation of surface roughness from texture features of the surface image using an adaptive neuro-fuzzy inference system", Precision engineering, Vo1.29, pp.95-100, 2005.

[15] Chengqing Yuan, Zhongxiao Peng, Xinping Yan, "Surface characterization using wavelet theory and confocal laser scanning microscopy", Journal of Manufacturing science and engineering Vo1.127, pp.394-404, 2005.

[16] B.Y.Lee, S.F.Yu, H.Juan, "The model of surface roughness inspection by vision system in turning", Mechatronics, Vol.14, pp.129-141, 2004.

[17] B.Y.Lee, H.Juan, S.F.Yu, "A study of computer vision for measuring surface roughness in the turning process", International Journal of advanced manufacturing Technology, Vo1.19, pp.295-301, 2002.

[18] B.Y.Lee, Y.S.Tarng, "Surface roughness inspection by computer vision in turning operations", International journal of machine tools and manufacture.VoI.41, pp.1251-1263, 2001.

[19] Xiaoou Tang, W.Kennth Stewart, "Optical and sonar image classification Wavelet packet transform vs. Fourier transform", Computer vision and image understanding, Vo1.79, pp.25-46, 2000.

[20] Marc Antonini, Michel barland, Pierre Mathieu, Ingrid Daubechies," Image coding using wavelet transform", IEEE transactions on image processing, Vol.1, No.2, 1992,

[21] B.Muralikrishnan, S.venkatachalam, J.Raja, M.Douglass, "Process mapping and functional correlation in surface metrology: a sheet metal case study", International Journal of advanced manufacturing Technology, Vo1.27, pp.75-82, 2005.

[22] Shing I.chang, JayakumarS.Ravathur, " Computer vision based non-contact surface roughness assessment using wavelet transform and response surface methodology", Quality engineering, Vo1.17, pp.435-451, 2005.

[23]JamesA.Freeman, DavidMskupra, "Neural networks: algorithms, applications, and programming techniques", Addison Wesley Longman Publishing Co., Inc.1991.