Research Paper

COMPARISON OF ARTIFICIAL NEURAL NETWORK APPROACH AND DATA MINING TECHNIQUE FOR THE PREDICTION OF SURFACE ROUGHNESS IN END MILLED COMPONENTS WITH TEXTURE IMAGES

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ABSTRACT:

This article presents a procedure for using machine vision data to predict surface roughness parameter of the end milled components. Stylus based surface roughness measurements were used and compared to vision based prediction of surface roughness. Wavelet decomposition was used to extract features from vision based data. In this article wavelet Energy features of approximations and details were extracted. The proposed method utilized two different classification techniques. M5P Decision tree was used as one of the technique to classify and correlate surface roughness of milled components. Artificial Neural network was another technique. The obtained surface roughness values were compared with the stylus type surface roughness measurement. It is found that artificial neural network classification outperforms the M5P decision tree.

KEYWORDS*:* Machine Learning, Machine Vision, Surface Roughness, Artificial neural Network, Decision Tree.

1. INTRODUCTION

Average surface roughness (R_a) has great influence on the performance of a finished part. The centre line average of peaks and valley of the machined surface has become one of the quantitative measures of a product quality. The surface topography is developed by the relative motion of tool and a work material during the material removal process. There are various parameters that influence surface roughness (Bernardo & Vosniakos , 2003).The development of non-contact type surface roughness measurement techniques have received much attention among researchers. As the life cycle of mold components reduces, lead time reduction with high quality becomes an important issue in the industry. End milling is one of the main operations used extensively to produce flat surfaces of precision die/ mold parts. Many researchers have proposed different approaches to predict surface roughness based on machining theory (Martellotti, 1941; Quintana et al.,2010), design of experiments (Gologlu & Sakarya,2008; Dhokia et al.,2008) and artificial intelligence (Abburi & Dixit,2006; Tsai et al.,1999). In-process system for surface roughness prediction in end milling operations using artificial Neural Networks was studied for CNC end milling with an accuracy of 90% (Tsai et al,1999;Lou et al,1998). They have used spindle speed, feed rate and depth of cut as input to the multiple regression model. But in another article, a method is developed to assess surface roughness using texture features derived from surface images (Lee et al.2004). Generally, texture analysis of image data can be performed in two ways, spatial and spectral approaches. Second order statistics derived from GLCM were calculated from spatial domain of images to assess surface roughness of the machined work pieces (Dedy Septiadi& Aulia MT Nasution,2009). In Spectral domain (Dhanasekar & Ramamoorthy,2010), Discrete Fourier Transform, STFT and Power Spectral Density were used to assess surface roughness. But, they yield satisfactory result for stationary signals. Many cases, surface image data are non-stationary signals. Wavelet Transform serves better result for non-stationary signals. An article devised quantitative measure of surface roughness was estimated in the spatial frequency domain using wavelet transform (Ramapriya & Srivatsa,2008). (Wei-Chen Li&Du-Ming Tsai,2012) developed discriminant measure for identifying defects on inhomogeneous solar wafers using wavelet coefficients. A research article presented classification of surface defects using image histogram features with machine learning algorithms (Ravikumar et al.,2011). The authors utilized C4.5 algorithm and Naïve Bayes algorithm for classification of histogram data.

In the present study, Surface images are captured from end milled samples. Wavelet energy values are extracted for wavelet decomposition of approximations and details. A Machine learning approach, M5P decision tree is used to classify surface roughness values. An Artificial Neural Network is constructed to correlate surface roughness data.

2. MACHINE LEARNING ALGORITHMS

Developing mathematical model for predicting surface roughness is a challenging task as it is highly interdependence between various parameters. In this paper, we proposed two different machine learning algorithms for predicting surface roughness of the machined components. They are M5P decision Tree and MLP- ANN. Since, these techniques are belongs to two different family, whose capability is tested in this articles. ANN is the algorithm that is opaque in nature produces a regression model. On the other hand, M5P Model tree produce understandable model with greater visibility.

2.1 M5P Decision tree

The M5P is a reconstruction of M5 algorithm for inducing trees of regression models. M5P modifies a conventional decision tree with the possibility of linear regression functions at the nodes. Model trees generate decision tree and with help of linear model at each node the prediction is performed. M5P Decision Tree algorithm can be considered for predicting surface roughness (Onyari & Ilunga,2013; Sarosh Hashmi et al.,2014). Wavelet energy features extracted from cropped images of captured image were given as input data set to the "Weka" software an model tree M5P algorithm were applied on the data set.

2.2 Artificial neural network

Artificial Neural network is mimicking behavior of human brain by connectivity approach.ANN can reproduce some functions of human behavior, which are performed by a finite number of layers with different computing elements called neurons. The organizations of Network determines the type and objectives of the ANNs.ANNs are widely used in many applications such as forecasting, control, data compression, pattern recognition and Vision systems(Asilturk & Cunkas,2011). An ANN has three layers: the input, hidden and output layers. Input and output layers are defined as nodes and the hidden layer provides a relation between input and output layers.

In this study, ANN architecture shown in Figure.1 is used for modeling and predicting surface roughness in end milling operations. The Back Propagation learning algorithm Lavenberg-Marquardt(LM) was used to update parameters in feed forward single hidden layer. The approximation wavelet energy, detail wavelet energy were used as seven neurons in the input layer. Output layer has single neuron representing predicted surface roughness. The various parameters such as learning rate, number of hidden layers, number of training and testing data and approximating function determine the accuracy, reliability and effectiveness of the neural network. "LOGSIG" Transfer function with single hidden layer has been used. The number of neurons in hidden layer was determined by trial and error procedure based on the MSE. This ANN architecture has 14 neurons in the hidden layer.

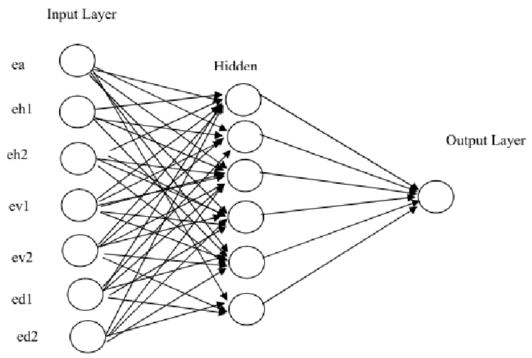

Figure 1. ANN architecture

Table 1 Experimental cutting condition

RUN	SPEED (rpm)	FEED (mm/min)	DOC (mm)
R1	1000	1000	0.6
R2	1000	1000	0.9
R3	1000	1000	1.2
R4	1000	1500	0.6
R5	1000	1500	0.9
R6	1000	1500	1.2
R7	1000	2000	0.6
R8	1000	2000	0.9
R9	1000	2000	1.2
R10	3000	1000	0.6
R11	3000	1000	0.9
R12	3000	1000	1.2
R13	3000	1500	0.6
R14	3000	1500	0.9
R15	3000	1500	1.2
R16	3000	2000	0.6
R17	3000	2000	0.9
R18	3000	2000	1.2
R19	5000	1000	0.6
R20	5000	1000	0.9
R21	5000	1000	1.2
R22	5000	1500	0.6
R23	5000	1500	0.9
R24	5000	1500	1.2
R25	5000	2000	0.6
R26	5000	2000	0.9
R27	5000	2000	1.2

3. MACHINE VISION SYSTEM

Machine Vision applications were used to extract information of the captured images. The implementation of Machine vision system in industries is to replace human intervention and decision making. High resolution cameras, advancement in interfacing hardware and software support the application of Machine Vision in almost all the fields. The Machine vision system broadly classified into three categories: they are measurement, guidance and inspection. In this study, Machine Vision inspection system determines whether an object or image matches a preset description (Uktu et al.,1998). The main components of machine vision system under study consist of: 1. Image acquisition system 2. Lighting system and 3 Data Processing module.

A CCD Camera with tele-centric lens is fixed in a fixture and positioned to view normal to the specimen surface. The samples were placed under camera keeping the relative position between camera and zoom level unaltered. An image of size 2048x1536 was captured. The image file size is of 9MB in Tiff format was stored. NI Vision assistant module was used to capture and store the images.

3.1 Image Pre processing

Acquired images may consist of noises and other artifacts. The images are preprocessed to be useful for feature extraction. The raw image first is converted into grayscale image. Then each image is applied with morphological opening operation followed by background subtraction and contrast equalization. Each image was cropped into 4 sub images for wavelet feature extraction. The sub image size is 200 pixels by 200 pixels. Four different sub images are obtained at different locations so that for one image we are able to extract four different set of image features can be obtained. A total of 108 set of features for 27 images were collected. Those values were given as input to both ANN and M5P algorithms.

Figure 2 depicts the image cropping process.

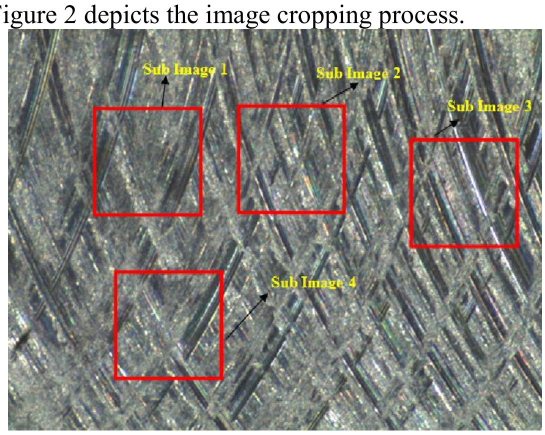

Figure 2 Image Cropping

4.2 Feature extraction

Feature Extraction is the computation of specific measures which represents the characteristics of any signal. The image features at different cutting conditions form the input to the classifier. To reduce the complexity in handling data points from images, researchers use few measures of the data points. Collection of such measures is called as feature extraction.

4.3 Wavelet features

A time-scale representation of the digital signal is obtained using digital filtering technique. The signal to be analyzed is passed through filters with different cut-offfrequencies at different scales. DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in Figure.3. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous time Multi-resolution to discrete-time filters.

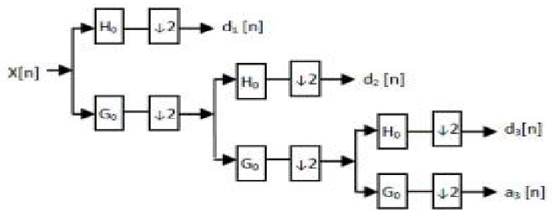

Figure 3 Wavelet Decomposition

In figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass, filter is denoted by G_0 while the high pass filter is denoted by H_0. At each level, the high pass filter produces detail information d[n], while the low pass filter associated with scaling function produces coarse approximations a[n].

In this study, Image captured from each cutting conditions were cropped into four different sub images ."Harr" mother wavelet was applied to each sub images at two decomposition levels. Wavelet energy features such as ea, eh1, ev1, ed1, eh2, ev2 and ed2 are computed and stored using Matlab 2009a version. ea refers to Energy of approximation coefficients; eh1and eh2 denotes energy of horizontal detail coefficients at level 1 and 2 respectively.ev1 and ev2 represent energy of vertical detail coefficients at level 1 and 2 respectively. Similarly, ed1 and ed2 refer to the energy of diagonal detail coefficients at level and 2 respectively. Table 2 depicts the various wavelet energy features extracted from the surface images. The wavelet energy features are given as input to both M5P classifier and ANN.

4. EXPERIMENTAL SETUP AND PROCEDURE

An AA 6061 aluminium alloy working specimen of size 50mmx 50mm x 20 mm was selected in this study because it is mostly used work piece material in the mold and die industry and other industries. End Milling Operation on specimens was carried out on a CNC Vertical Machining Centre. The cutting tool was a twist fluted 12.5 mm diameter end mill cutter with TiN coating was done by Physical Vapour Deposition.

The Experimental Data was produced by changing the cutting conditions speed, feed rate and depth of cut. The experimental machining involved 27 trials with three cutting conditions developed in three levels. A Surfcoder (SE3200) was used to measure surface roughness (Ra) after end milling operation. The cut off length for measurement was kept as 0.8 mm per stroke. Four different reading were taken for each samples along the direction of lay. The average was used to train the machine learning algorithms such as ANN and M5P decision tree. All the experimental data is tabulated in Table 1.

Table 2 Some of the wavelet energy features input variables for classifier

Run	ea	eh1	eh2	ev1	ev2	ed1	ed2
r1	99.61939	0.02488	0.0656	0.066956	0.212735	0.002734	0.007699
r2	99.75515	0.022863	0.060446	0.038293	0.11324	0.003	0.007008
r3	99.50104	0.027085	0.073951	0.090507	0.295465	0.003412	0.008543
r4	99.57546	0.028619	0.079645	0.073666	0.230053	0.003179	0.009379
r5	99.53098	0.027144	0.068971	0.085067	0.275705	0.002897	0.009242
r6	99.74793	0.030705	0.08367	0.033255	0.091706	0.003247	0.009489
r7	99.67926	0.016721	0.039372	0.061129	0.195322	0.002586	0.005612
r8	99.64676	0.022879	0.056183	0.063946	0.199474	0.003335	0.007424
r9	99.70045	0.019099	0.045903	0.054648	0.170826	0.002537	0.006537
r10	99.77006	0.018012	0.041426	0.041616	0.120073	0.00311	0.005705
r11	99.57196	0.066346	0.216388	0.033873	0.093489	0.004777	0.013172
r12	99.77718	0.022069	0.057722	0.034051	0.100014	0.00272	0.006239
r13	99.57913	0.024984	0.062265	0.076906	0.244001	0.003279	0.009439
r14	99.603	0.027324	0.072761	0.068853	0.216356	0.003651	0.008056
r15	99.78968	0.021002	0.053597	0.03231	0.093975	0.002831	0.006602

5 RESULTS AND DISCUSSIONS

Machine learning techniques like Artificial Neural network or a model tree will perform well when it learnt the properties of data set under training and classifies the new data. The performance of those techniques can be measured by root mean square error and the correlation coefficient.

5.1 *Results of M5P model tree*

The Figure.4 depicts the model tree constructed by M5P algorithm.M5P model tree predicts surface roughness data by forming piecewise linear functions at leaves. This model tree produces a root mean squared error of 0.2297 and correlation coefficient of 0.8937.

5.2 *Results of artificial neural network*

The Matlab Neural Network Tool box was used to train the wavelet energy data and validate the surface roughness values for the set of wavelet energy data. Performance of the neural network related to hidden layer and number of neurons in a hidden layer, activation functions and training algorithm parameters.

Neither Very Less number of neurons in the hidden layer nor large number of neurons in hidden layer yields good approximations. A balance between too many or too few neurons in the hidden layer must be obtained. Most of the literatures (Quintana et al,2011) employ trial and error method to fix the number of neurons in the hidden layer. In this article, feed forward back propagation net work structure was used Lavenberg-Marquardt training function 'trainlm' and 'tansig' learning function was adapted for the network training. Sample data was introduced as input attributes to the network and experimentally measured surface roughness values corresponding to each machined surface in turn the captured images as target to the network. During training the network architecture is adjusted according to the error. Validation data measures network generalization. Training continues till network's error reduces in respect of validation data.

A number of ANN were constructed, trained and tested by varying number of neurons in the hidden layer with the wavelet energy data. Among those networks, a network with 14 neurons in the hidden layer found to be best. Figure. 5 show the regression curve drawn between output and target values. Outputs given by the neural network are plotted against the given target at the time of training. The empty circle in the plot denotes target- and output relationship. The correlation measure R=0.98215. The network gives correlation value of 0.99946 during training, 0.93931 during validation and 0.95099 during testing.

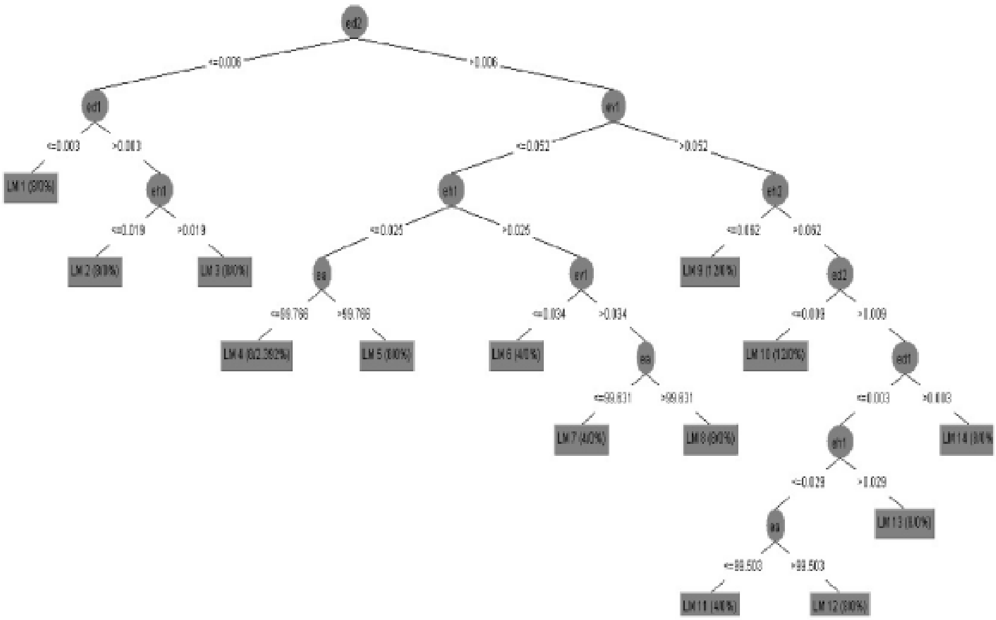

Figure 4. Decision Tree by M5P Algorithm

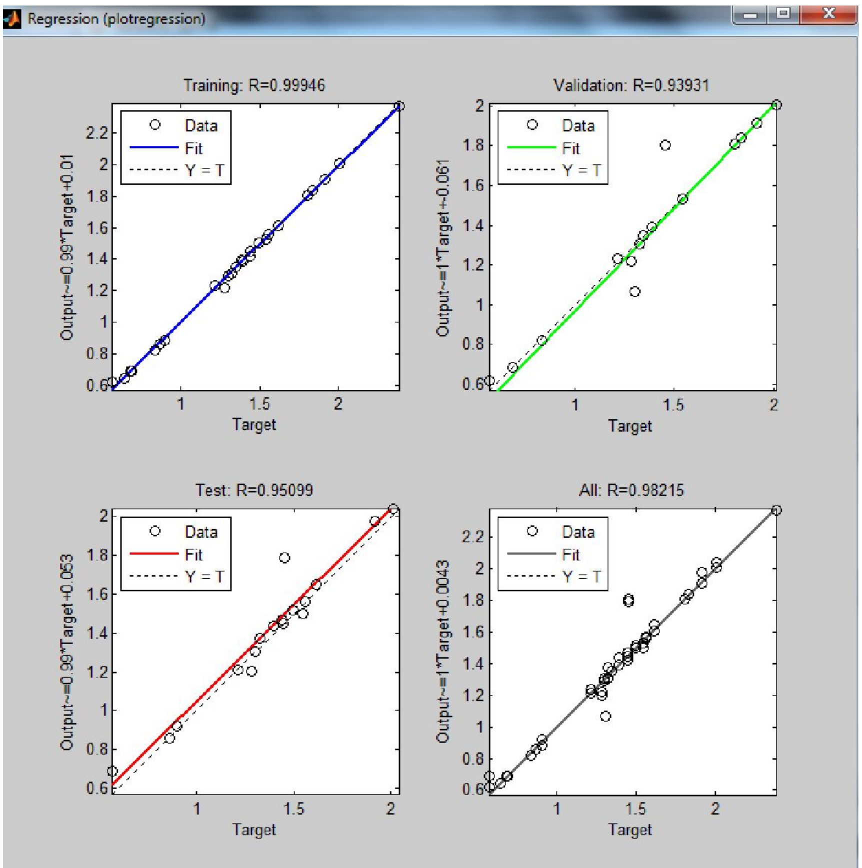

Figure 5. Regression plot of Artificial Neural Network

Figure. 6 show the comparison of the surface roughness both Machine learning techniques in respect of stylus measurement. The Figure.6 clearly depicts BP-ANN outperforms the M5P decision Tree.

Table 3 represents the comparison of surface roughness values obtained by both M5P Decision Tree and ANN. Also, Table 4 describes the performance measures of M5P Decision Tree and ANN.

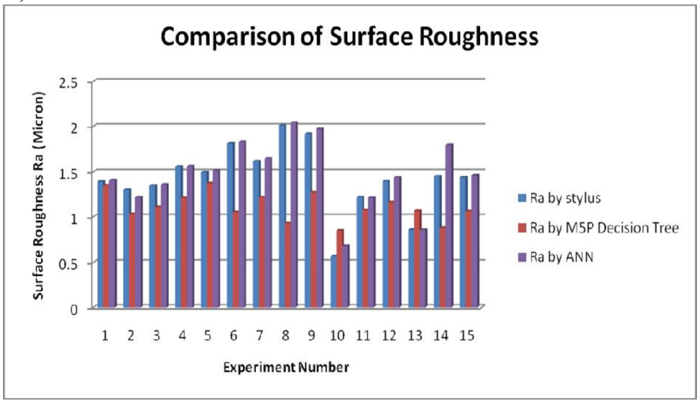

Figure.6 Histogram plot of Surface roughness values

Table 3 Comparison of Surface roughness values of few experiments

Experiment Number	Surface Roughness values by Experiment Ra µm	Surface Roughness values by M5P Decision Tree Ra µm	%Error	Surface Roughness values by ANN Ra µm	%Error
1	1.391	1.351	2.90	1.406	-1.04
2	1.303	1.034	20.63	1.216	6.67
3	1.347	1.109	17.63	1.358	-0.85
4	1.56	1.212	22.30	1.566	-0.37
5	1.497	1.375	8.18	1.518	-1.38
6	1.807	1.053	41.75	1.824	-0.96
7	1.617	1.217	24.73	1.649	-1.95
8	2.011	0.931	53.71	2.041	-1.48
9	1.915	1.273	33.51	1.976	-3.19
10	0.569	0.854	-50.13	0.686	-20.56
11	1.216	1.075	11.60	1.212	0.36
12	1.394	1.161	16.74	1.439	-3.19
13	0.864	1.066	-23.36	0.861	0.32
14	1.453	0.881	39.39	1.791	-23.28
15	1.442	1.062	26.36	1.467	-1.73

In Table 4 the performance measures such as RMSE and correlation coefficient of the M5P Decision Tree and BP-ANN are tabulated. The Table 4 clearly explains that BP-ANN has higher correlation coefficient than M5P Decision tree algorithm. But, Root mean square error found to be high in BP-ANN.

Table 4 Comparison of Performance measures of M5P and BP-ANN

Machine learning Technique	Root Mean Square Error	Correlation Value
M5P Decision Tree	0.2297	0.8937
BP-ANN	0.7050	0.98215

6 CONCLUSIONS

In this research the usefulness of M5P Decision Tree and Artificial Neural network was discussed in indirect measurement of surface roughness values by end milling operation. This article uses Wavelet energy data derived by capturing images from machined surfaces. This methodology leads to online monitoring of surface roughness with no prerequisite known cutting conditions. Out of M5P decision Tree and ANN, Artificial neural network correlate experimentally measured surface roughness very closely.

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