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Machine Learning Approach to the Prediction of Surface Roughness using Statistical Features of Vibration Signal Acquired in Turning

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Abstract

Prediction of surface roughness is always considered important in the manufacturing field. A product may require a particular roughness that may be specified by the designer for various reasons, either functional requirement or aesthetic appeal. While modern manufacturing systems and machines have always contributed towards better control of surface quality, better computational facilities and the availability of newer algorithms attract researchers to understand the prediction of quality in a better manner. In this paper, prediction of surface roughness by multiple regression analysis is presented. The predictors are cutting parameters, tool wear and the statistical parameters extracted from the vibration signals of a turning centre. The contribution of various statistical parameters in prediction of surface roughness is studied. A Machine learning approach using feature reduction using principle component analysis is attempted to achieve higher predictability and low computational effort.

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1. Introduction

Surface roughness is a function of cutting parameters, machine rigidity, tool condition, work material property, tool vibration *etc.* It is an index of the quality of surfaces obtained from different process of manufacture. A product may require a particular roughness that may be specified by the designer for various reasons, either functional

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requirement or aesthetic appeal. Thus, studies have been made to quantify the surface roughness and identify the process and the capability of the machine. When any one of the parameters exceeds a certain limit, the surface quality suffers. Moreover, keeping all other parameters constant, the vibration signals may serve as a direct indicator of the surface roughness. A study can be performed at various cutting conditions and tool conditions (flank wear) to establish a relation between surface roughness and vibration. Many researchers have contributed to the study of vibrations and its implication on the surface roughness. Rehorn *et al.* had reviewed the work of many researchers who had used different kinds of sensors and signal processing methodologies during condition monitoring of tool in various machining operations[1]. Shinn-Ying Ho *et al.* have proposed an adaptive neuro-fuzzy inference system (ANFIS) using computer vision method and have established a relationship between the features of surface image and the actual surface roughness[2]. Sidda Reddy *et al.* developed a model for the prediction of surface roughness during aluminum alloy turning using the same system[3]. Lin *et al.* used a network to formulate a prediction model for surface roughness and cutting force and claims that this model is more accurate than that by regression analysis[4]. Surjya K. Pal *et al.*, have used the back propagation neural network model to predict the surface roughness in turning operation with a HSS tool and compared the predicted and the measured values[5]. Salgado *et al*. have used least-squares support vector machine to estimate the surface roughness given the cutting conditions and the features extracted from the vibrations signals[6]. Daniel Kirby *et al.* have used only the mean of the vibration signal in the prediction of surface roughness in turning operation[7]. To sum up the literature survey, researchers use force as parameter along with cutting parameters for predicting surface roughness while others use vibration signals. On careful observation, vibration as a parameter is more sensitive to very minor variations in the causes of surface roughness. The wear on the flank of the tool also affects the surface roughness adversely. This leads to deterioration in the surface quality. Based on the above, one may agree that any study on surface roughness prediction cannot ignore the flank wear as a parameter as well as the resulting vibrations. This gives the fundamental motivation to take up regression modeling of surface roughness using flank wear along with cutting parameters and vibrations.

This study intends to predict surface roughness in turning operation, using machining parameters (speed, feed, depth of cut (DOC)), tool wear (flank wear) using multiple linear regression (MLR) and by including the following statistical features extracted from the vibration signal and discussed in four cases by including

- only the mean of the vibrations (Case 1)
- the first four moments of the statistical features (Case 2)
- all the statistical features (Case 3)
- statistical features selected by Principle Component Analysis (PCA) (Case 4)

2. Experimental Design

81 experiments *(3 X 3 X 3 X 3)* were conducted by varying the cutting parameters along with three different flank wear (*viz.* new tool, flank wear 0.2 mm and flank wear 0.4 mm) of the tool. The spindle speed was set at 500 rpm, 700 rpm and 900 rpm and for each speed; the feed was set at 0.05 mm/sec, 0.7 mm/sec and 0.09/sec. For each speed and feed combination, the depth of cut was kept at 0.5 mm, 0.8 mm and 1.2 mm. The Table 1 shows the experimental design matrix.

Table 1- Parameters varied for the study of surface roughness

Speed (rpm)	Feed (mm/sec)	DOC (mm)	Flank Wear (mm)
500	0.05	0.5	0.0
700	0.07	0.8	0.2
900	0.09	1.2	0.4

2.1 Experimental setup

The experimental setup shown in Fig.1 consists of a CNC turning center, a piezoelectric accelerometer, a signal acquisition unit, a FFT analyzer, a computer to record signals and surface measurement unit. The CNC machine - DX200 with a controller system of SINUMERIK - 802D is a product of Jyothi CNC, Gujarat, India, and the one used for the experiment has the following specifications:

Max Turning Length/Diameter/Swing over bed	: 500 mm/350 mm/ 500mm
Speed Range	: 50 - 4000 rpm
Spindle Motor Power (Continuous rating/30 min. rating)	: 9 kw/ 12 kw

2.2 FFT analyser and accelerometer setup

The piezoelectric accelerometer (Dytran model) was directly mounted on the tool holder using an adhesive. The accelerometer was then connected to the signal-conditioning unit (DACTRAN FFT analyzer), where the signal goes through the charge amplifier and an Analog-to-Digital Converter (ADC). The vibration signals in digital form were input to the computer through an USB port. RT-Pro-series software was used for recording the signals directly to the computer's secondary memory. The signal was then read and processed to extract different statistical features as mentioned in Section 3.

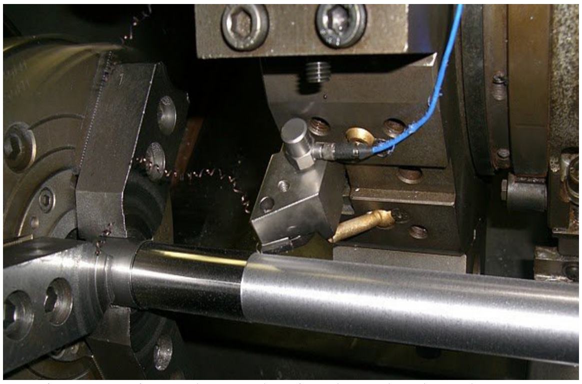

Fig. 1 Experimental setup showing the tool and accelerometer

2.3. Tool tip preparation

The tools used were carbide inserts **TNMG160408.** There were three different stages of wear on the flank that were used. Apart from using brand new carbide tipped tool, tool tips of the same grade and make but with a flank wear of 0.2 mm and 0.4 mm were used. The tool tips with flank wear were measured using an optical measuring instrument which had a computerized digital image on the screen with crosswire and a digital readout. From various used tool tips, those with the flank wear of 0.2 mm and 0.4 mm were segregated and used.

2.4 Experimental procedure

The procedure to acquire signals consisted of mounting an unused new carbide tool tip (**TNMG160408)** in a tool holder and was fixed on the tool post. The accelerometer was fixed on the tool holder using adhesive mounting technique as shown in the Fig. 1. The signal acquisition parameters like sampling frequency (24 kHz), sampling length (8192), type of signal (amplitude only in text format) *etc*., were set. The highest frequency was found to be 12 kHz and since Nyquist sampling theorem says that the sampling frequency must be twice that of the highest measured frequency, it was chosen to be 24 kHz. The 20 mm EN8 steel rod was clamped at the live center and a rough turning was carried out to remove the top layer that had undergone oxidation and smoothen out the surface of the rod. The data acquisition system was switched on and first few signals were ignored purposefully to avoid initial random variation and on stabilization of the process 150 signals were acquired.

2.5 Data acquisition

The vibration signal from the piezoelectric pickup mounted on the tool holder was recorded after allowing the turning process to stabilize for sometime (about 1 min). The sampling frequency was 24 kHz and the sample length was 8192 for all conditions. The sampling length was chosen as 8192 which is equal to 2^{13} which is around 10000 readings. The data consists of cutting parameters, flank wear, vibration signal parameters and the corresponding surface roughness '*Ra*' value. The experimental design has been explained earlier in section 2. In order to study the influence of flank wear on prediction of surface roughness, all three surface roughness values for a given cutting condition was grouped together (flank wear of 0 mm, 0.2 mm and 0.4 mm). This enables the regression model to take care of variation in the flank wear. For each cutting condition and flank wear, 150 vibration signals and the corresponding surface roughness *'Ra'* value were recorded. The minimum Ra value for the measured experiment is 1.07microns and the maximum is 3.92 microns. The minimum Ra value for the predicted surface roughness obtained from the regression equation is 1.14 microns and the maximum is 3.89 microns.

3. Statistical Features

From the time domain signals acquired the statistical features are extracted. The statistical analysis of vibration signals yields different parameters. The statistical parameters taken for this study are mean, standard error, median, standard deviation, sample variance, kurtosis, skewness, range, minimum, maximum and sum. Thus, the statistical features were calculated for the 150 signals acquired for each condition.

4. Methodology

In order to build a prediction model for the surface roughness, details about the cutting parameters and the vibration signals are required. In addition, for each set of cutting parameter and vibration level, the corresponding surface roughness was measured. The cutting parameters and acquisition of vibration signals have already been explained in section 2.5. The surface measuring instrument used is a stylus type probe which takes three readings of 0.25 mm over a length of 2.5 mm and calculates the average *'Ra'* value. This data is used to build a prediction model using multiple regressions. The details of building the model and regression are described in section 6.

5. Dimensionality Reduction using PCA

Principal component analysis (PCA) is one of the widely used multi dimensional features reduction tool. PCA is one of the preferred choices as it is a simple and non-parametric method of extracting relevant information from complex data sets. The purpose of PCA is to reduce the dimensionality of the data while preserving as much as possible of the variations in the original dataset. It transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate, the second greatest variance on the second coordinate, and so on. PCA can be used for dimensionality reduction for a dataset while retaining the characteristics of the dataset that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Elangovan et al. discussed the use of PCA and Decision Tree with various classifiers to reduce the data dimensionality and reported improvement in classifier efficiency[8] Similarly, Sakthivel et. al compared the various other dimensionality reduction techniques with PCA[9]. Hence PCA was carried out on the data.

6. Regression Analysis

The regression equation is an algebraic representation of the regression line used to describe the relationship between the response and predictor variables. Multiple regression is a statistical technique that allows us to predict the criterion variable on the basis of several other predictor variables. The regression equation takes the form: Response = constant + coefficient (predictor1) + ... + coefficient (predictor (*n*)) or $Y = bo + b1X1 + b2X2 + ... + bkXk$, where Y is the value of the response. Constant (bo) is the value of the response variable when the predictor variable(s) is zero. The constant is also called the intercept because it determines where the regression line intercepts the Y-axis. Predictor(s) *(X)* is the value of the predictor variable(s). Coefficients (b1, b2, ... , bk) represent the estimated change in mean response for each unit change in the predictor value. In other words, it is the change in Y that occurs when X increases by one unit. R is a measure of the correlation between the observed value and the predicted value of the criterion variable. R Square (R^2) is the square of the measure of correlation and indicates the proportion of the variance in the criterion variable which is accounted for by the developed model. This is a measure of how good a prediction of the criterion variable we can make by knowing the predictor variables. However, R

square tends to somewhat over-estimate the success of the model when applied to the real world, so an Adjusted *R* Square value is calculated which takes into account the number of variables in the model and the number of observations (participants) our model is based on. This Adjusted *R* Square value gives the most useful measure of the success of our model.

7. Results and Discussions

Multiple regression was carried out to predict the surface roughness of the turned shaft using a non-coated tipped carbide tool. The results are discussed using four cases as mentioned in section 1.

Case 1: The regression equation obtained when the cutting parameters (speed, feed, depth of cut) and the first (mean) of the statistical features from vibration signal along with the flank wear is given as *sr = 5.51 - 0.00253 speed - 3.78 feed - 1.47 doc + 0.759 Mean + 0.311 fw , w*here, *sr* is the surface roughness and *fw* is the flank wear of the tipped tool.

Case 2: The regression equation obtained when the cutting parameters (speed, feed, depth of cut) and the first (mean), second (standard deviation), third (Kurtosis) and fourth (Skewness) moments of the statistical features from vibration signal along with the flank wear is given as:
sr = 5.66 - 0.00268 speed - 2.96 feed - 1.48 doc + 1.09 Mean + 0.501 fw - 0.272 Standard deviation + 0.00392 Skewness + 0.000112 Kurtosis

Case 3: The regression equation obtained when the cutting parameters (speed, feed, depth of cut) and the statistical features of the vibration signal (mean, standard error, median, standard deviation, sample variance, kurtosis, skewness, range, minimum, and sum) along with the flank wear is given as:
sr = 5.82 - 0.00292 speed - 3.42 feed - 1.41 doc + 91.4 Mean+ 25203748 standard error - 1.37 Median - 278465 Standard deviation + 0.000118 Kurtosis + 0.00401 Skewness - 0.0350 Range - 0.0110 Sum + 0.511 fw

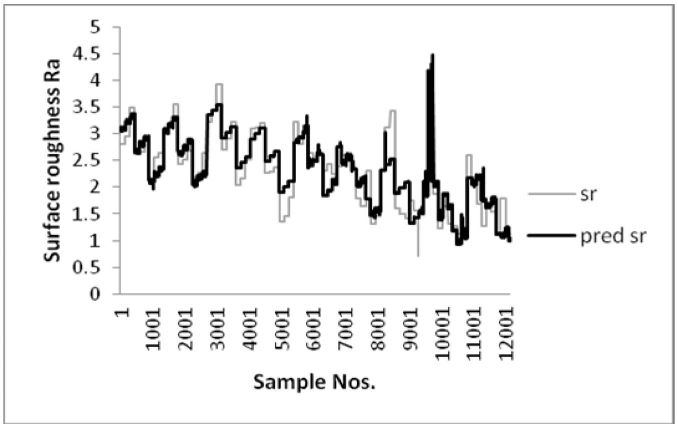

Fig. 2 Full set – carbide tipped tool – sr and predicted sr

In the present Case 3, the value of S = 0.311009, R-Sq = 80.8% and R-Sq (adj) = 80.8%. The surface roughness plotted against the sample nos. for predicted and measured surface roughness is plotted in Fig. 2. The Analysis of Variance is given in Table 2.

Table 2. Anova results for Case 3 of full set – carbide tipped tool

Source	DF	SS	MS	F	P
Regression	12	4953.16	412.76	4267.32	0.000
Residual Error	12137	1173.97	0.10		
Total	12149	6127.13			

Case 4: The regression equation obtained when the cutting parameters (speed, feed, depth of cut) and the statistical features of the vibration signal selected by using PCA along with the flank wear is given as: *sr = 5.66 - 0.00266*

speed - 3.09 feed - 1.47 doc + 0.000096 Kurtosis - 0.0411 Range + 0.491 fw
The Analysis of Variance is given in Table 3.

Table 3. Anova results for Case 4 of full set – carbide tipped tool

Source	DF	SS	MS	F	P
Regression	6	4547.54	757.92	6042.57	0.000
Residual Error	12143	1523.10	0.13		
Total	12149	6070.64			

From the values presented in Table 4, we find that Case 4 has lower RMSE value and the correlation coefficients are higher compared to Case 1 and Case 2. Case 4 represents the values obtained after the statistical features have been reduced using PCA. As expected, since all the features are included, Case 3 has the highest correlation coefficient of 80.8%, but the RMSE value is 0.539644 and the computation time is the largest as all features are included. However, this reveals that all the statistical features given in the equation under Case 3 contribute to the prediction of the surface roughness and when the features are eliminated, the regression equation becomes more approximated. Convincingly, Case 4 has a lower computational effort than Case 3 as well as a lower *'S'* value.

Table 4. Consolidated results of three cases of Carbide tipped tool

Condition	S	R-Sq%	R-Sq(adj) %	RMSE
Case 1	0.384792	70.7	70.6	0.666385
Case 2	0.355749	74.9	74.9	0.615976
Case 3	0.311009	80.8	80.8	0.539644
Case 4	0.354162	74.9	74.9	**0.354069**

'S' = 0.354162 represents the standard distance data values fall from the regression line and is measured in the units of the response variable. For the given study, the lower 'S' value, the better the equation predicts the response. Thus, the influence of statistical parameters of the vibration signal on the regression equation were used for predictability of roughness based on the cutting parameters, tool wear and the statistical features extracted from the tool vibrations in a turning operation is better. The RMSE (root mean square error) value between the predicted and the actual measured surface roughness was 0.354069.

8. Conclusion and Future Scope of Work

Thus, the statistical features extracted from the time domain signals using Machine Learning approach play an important role in enhancing the reliability of the regression equation. When we compare the cost involved in other systems, the accelerometer based data acquisition is very cost effective. The computational effort is the lowest when the feature reduction of statistical features is carried out using PCA and with a reasonable predictability. This approach is useful in the development of online surface roughness prediction using pattern recognition. Further, different feature reduction methods along with other regression techniques may be attempted.

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