Developing Gaussian Process Model to Predict the Surface Roughness in Boring Operation

Balamuruga Mohan Raj. G#1, Sugumaran. V#2

#1Research Scholar, Dept. of Mechanical Engineering, Karpagam University, Coimbatore, India.
Associate Professor, Sri Manakula Vinayagar Engineering College, Puducherry, India.
#2Associate Professor, SMBS, VIT University Chennai, Tamil Nadu, India

Abstract—In machining industries, achieving better surface finish of a product is very essential. Surface finish is important in terms of tolerances, it reduces assembly time in mating surfaces which results in overall cost reduction. In this work, three cutting speeds, three feed rates and three depth of cuts were used in boring operation. During the boring operation, the accelerometer was fixed on the tool post to record the vibration signal. The surface roughness was measured using perthometer. Finally the Gaussian Process regression model has been developed to predict the surface roughness based on tool post vibration and cutting conditions.

Keywords—Surface roughness prediction, Gaussian Process, Boring operation, Vibration.

I. INTRODUCTION

The demand to manufacture low cost products with better quality has forced the manufacturing industry to continuously progress in machining technologies. Surface roughness is a measure to determine the quality of a product in boring for cams and crankshaft holes in engine blocks. Boring is an internal turning process and differs from external turning operations in many ways. In external turning, a tool is normally short and rigidly clamped, whereas in boring operations a long and slender tool is used. Hence, the mechanism behind the formation of the surface roughness in boring is very dynamic, complicated and process dependent. The dynamic nature and widespread usage of boring operations in general engineering applications has raised a need for seeking a systematic approach that can help to set up boring operation in a timely manner and also to help achieve the desired surface roughness with less cost. Long and slender boring bars statically and dynamically deform under the cutting forces acting on the rake face of the tool during boring operations. Due to this deflection, dimensional accuracy and surface roughness do suffer as depth of cut may vary, making this process complicated in nature.

Though the surface roughness in machining processes such as turning, drilling and milling ([1],[2],[3]) has been studied widely, the boring process is investigated by a few researchers only. In boring, some researchers modeled the mechanics and dynamics of a boring process for single point boring bar ([4],[5]) and multi inserts boring head using the computer simulation packages. These models were not general enough for the general industrial applications. They claimed that these models could be used in the process planning of boring operations to predict the surface roughness and dimensional accuracy. The existing surface roughness investigation methods are discussed below.

A ceramic (Si3N4) cutting tool was used in high speed turning on gray cast iron which results in good surface finish [6]. Surface integrity was investigated in rough machining of Titanium alloy with carbide cutting tool under dry cutting conditions [7]. In milling operation, the influence of cutting parameters on surface roughness was studied in the medium density fibre board [8]. In boring operation, by selecting proper cutting conditions, cutting forces can be controlled below a threshold value, cycle time can be shortened and tool life can be increased; therefore, the boring process in engine can be reduced significantly[9]. Surface roughness could be predicted by taking feed rate, cutting speed, depth of cut and vibration signals of tool holder as input parameters in the CNC Lathe turning operation with the help of ANN [10]. Surface quality of the machined part was studied based on high speed cutting parameters under dry turning of super alloy Inconel 718 [11].

Taguchi method is used to minimize the roughness by investigating the rake angle effect on roughness in boring performed on a CNC lathe [12]. Model of machining error caused by tool deflection was studied in the internal boring process [13]. A reliable surface roughness monitoring application was developed based on an ANN approach for vertical high speed milling operations with considering geometrical cutting factor, part geometries, lubricants, materials and machine tools [14].

Based on the literature survey, the surface roughness prediction based on cutting conditions, surface roughness improvements using various tool materials, rake angle, coolant were studied and reported for mainly turning operation and to some extent milling operations. The results of turning and milling operations are directly not applicable for
boring operation. This is mainly due to drastic change in tool geometry and tool length. Hence, there is a clear need to study the relationship between surface roughness and its affecting parameters. The presence study deals the regression model built using Gaussian Process for the purpose of predicting surface roughness using cutting conditions (speed, feed and depth of cut) and tool post vibration.

II. EXPERIMENTAL SETUP

The experimental setup, shown in Fig.1 was used for obtaining the vibration signals during a boring operation. The set up consisted of a CNC turning center, a piezoelectric accelerometer, a signal acquisition and signal conditioning unit and a computer to record the signals. The specification of accelerometer is given in Table 1.

Table 1. Specification of accelerometer.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Make</td>
<td>Dytran Instruments Inc. USA</td>
</tr>
<tr>
<td>Model Number</td>
<td>3035B1</td>
</tr>
<tr>
<td>Weight</td>
<td>2.5g</td>
</tr>
<tr>
<td>Range</td>
<td>0 – 500 g</td>
</tr>
<tr>
<td>Frequency</td>
<td>0.5 – 10 kHz</td>
</tr>
<tr>
<td>Resonance</td>
<td>45 kHz</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>10 mV/g</td>
</tr>
</tbody>
</table>

2.1. Data Acquisition

A piezoelectric accelerometer is a transducer which gives information about the machine vibration. The accelerometer was connected to a NI-DAQ card (data acquisition card – NI USB 4432). The data acquisition card was connected to a computer through USB port. To acquire the vibration signals National Instruments LabVIEW (software) was used. The sampling frequency was set to 24 kHz and the sample length was chosen as 2000 samples per signal. The sampling frequency was fixed based on the Nyquest sampling theorem. The sample length was fixed arbitrarily to some extent; however, the following points were considered. The features like mean, minimum value, and maximum value will be extracted from the signals and used as measures for regression analysis. In order to have meaningful features, the number of samples should be high. If the sample length is too high, then the computation effort required will be more for no much gain. To strike a balance, sample length of 2000 was fixed.

2.2. Parameters for Machine Condition

There are many parameters useful for machine condition like vibration, noise, acoustic emission etc., as discussed in chapter 1. Amongst them, vibration is used in the present study. Vibration is a special type motion; to and fro repetitive motion. Vibration is characterized by various parameters like displacement, velocity and acceleration. The decision as to which of these three to be monitored is strongly influenced by the frequencies, which are to be measured. In order to ensure that electrical interference (electrical noise) does not obscure the vibration signal, a large signal is desirable, giving a high ‘signal-to-noise’ ratio. The amplitude of the vibration parameters also varies with rotational speed of the shaft (work piece). It is an important consideration in transducer selection. Velocity increases in direct proportion to speed, while acceleration increases with the square of speed. From this, the following conclusions can be drawn:

- Acceleration is not a good choice for very low frequency analysis, while displacement does not work well for high frequencies.
- Velocity can be used for general monitoring purpose, where a vibration limit can be set independent of frequency.

As the speed of shaft in the study is fairly high, acceleration will give high amplitude signal with high ‘signal-to-noise’ ratio. Hence, acceleration of vibration is chosen for chatter measurement in the present study. Accelerometers give the acceleration directly in the form of voltage signal.

2.3. Accelerometer Mounting

In many applications, transducer mounting is as important as the selection of the transducer itself. If the motion of the test structure is not accurately transmitted to the transducer, it cannot be accurately measured. Any mounting method different from that used for calibration should be characterized for its dynamic characteristics over the intended frequency and amplitude range. The recommended mounting method for shock and vibration measurements is that used for calibration. There are three mounting methods typically used for monitoring applications viz., bolt mounting, glue mounting and magnetic mounting. In this study glue mounting is used. The adhesive or glue mounting method provides a secure attachment without extensive machining. However, this mounting method will typically reduce the operational frequency response range. This reduction is due to the damping qualities of the adhesive. Hence, the amount of adhesive used is to be kept to the minimum to minimize its effect. In the study here, the adhesive used was less than 0.2 g. compared to the weight of the sensor (2.5g), it is very small; further, the adhesive is spread over an area of 78.5 mm² (Approx.) . Hence, its damping effects can be ignored. Surface cleanliness is of prime importance for proper adhesive bonding.

2.4. Data Acquisition Hardware

A piezoelectric accelerometer (Dytran make) is mounted on the flat surface using direct adhesive mounting technique. The voltage output of accelerometers is proportional to acceleration. Accelerometers are the preferred transducers in machine condition monitoring due to the following reasons: extreme ruggedness, large frequency response and large dynamic range. Accelerometers can detect very small vibrations without being damaged by large vibrations; output
is proportional to forces which are the cause of internal damage and high-frequency sensitivity.

The accelerometer is connected to National Instruments make sound and vibration acquisition card, where the signal goes through the charge amplifier and then an Analogue-to-Digital Converter (ADC). The vibration signal in digital form is input to the computer through an USB port. It is stored directly in the computer secondary memory. The signal is then read from the memory and processed to extract different features. The extracted features are explained in the section IV.

From the vibration signals, descriptive statistical parameters such as mean, median, mode, kurtosis, skewness, standard error, standard deviation, minimum, maximum, sum, and range are computed to serve as features. They are named as ‘statistical features’ here. Brief descriptions about the extracted features are given below.

(a) **Standard Error**: Standard error is a measure of the amount of error in the prediction of \( y \) for an individual \( x \) in the regression, where \( x \) and \( y \) are the sample means and \( n \) is the sample size.

\[
\text{Standard error of the predicted, } Y = \sqrt{ \frac{1}{n-2} \sum (y - \bar{y})^2 - \frac{\sum (x - \bar{x})(y - \bar{y})^2}{(n-1)s^2}}
\]

(b) **Standard Deviation**: This is a measure of the effective energy or power content of the vibration signal. The following formula was used for computation of standard deviation.

\[
\text{Standard Deviation} = \sqrt{\frac{\sum x^2 - (\sum x)^2}{n(n-1)}}
\]

(c) **Sample Variance**: It is variance of the signal points and the following formula was used for computation of sample variance.

\[
\text{Sample Variance} = \frac{\sum x^2 - (\sum x)^2}{n(n-1)}
\]

(d) **Kurtosis**: Kurtosis indicates the flateness or the spikiness of the signal. Its value is very low for normal condition of the bearing and high for faulty condition of the bearing due to the spiky nature of the signal.

\[
\text{Kurtosis} = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \left\{ \frac{\sum (x - \bar{x})^4}{s^4} \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}
\]

where ‘s’ is the sample standard deviation.

(e) **Skewness**: Skewness characterizes the degree of asymmetry of a distribution around its mean. The following formula was used for computation of skewness.

\[
\text{Skewness} = \frac{n}{n-1} \sum \left( \frac{x - \bar{x}}{s} \right)^3
\]

(f) **Range**: It refers to the difference in maximum and minimum signal point values for a given signal.

Fig. 1. Experimental Setup

### III. PROCEDURE

The work piece made up of mild steel shaft of internal diameter 15 mm and outer diameter 30 mm was mounted in the machine. Then a single point boring tool (specification) with carbide tip was selected. This tool has a very high hardness capable of machining harder work pieces. This tool was kept as a reference tool for the boring operation. After the tool was selected, the cutting conditions were chosen as in the Table 2.

<table>
<thead>
<tr>
<th>Speed (rpm)</th>
<th>Feed (mm/rev)</th>
<th>DoC (mm)</th>
<th>Speed (rpm)</th>
<th>Feed (mm/rev)</th>
<th>DoC (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>0.5</td>
<td>0.5</td>
<td>700</td>
<td>0.7</td>
<td>1.2</td>
</tr>
<tr>
<td>500</td>
<td>0.5</td>
<td>1.2</td>
<td>700</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>500</td>
<td>0.7</td>
<td>0.5</td>
<td>900</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>500</td>
<td>0.7</td>
<td>1.2</td>
<td>900</td>
<td>0.5</td>
<td>0.8</td>
</tr>
<tr>
<td>500</td>
<td>0.9</td>
<td>0.5</td>
<td>900</td>
<td>0.7</td>
<td>1.2</td>
</tr>
<tr>
<td>500</td>
<td>0.9</td>
<td>0.8</td>
<td>900</td>
<td>0.7</td>
<td>0.5</td>
</tr>
<tr>
<td>500</td>
<td>0.9</td>
<td>1.2</td>
<td>900</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>700</td>
<td>0.5</td>
<td>0.5</td>
<td>900</td>
<td>0.7</td>
<td>1.2</td>
</tr>
<tr>
<td>700</td>
<td>0.5</td>
<td>0.8</td>
<td>900</td>
<td>0.9</td>
<td>0.5</td>
</tr>
<tr>
<td>700</td>
<td>0.5</td>
<td>1.2</td>
<td>900</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>700</td>
<td>0.7</td>
<td>0.5</td>
<td>900</td>
<td>0.9</td>
<td>1.2</td>
</tr>
<tr>
<td>700</td>
<td>0.7</td>
<td>0.8</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As the tool touches the work, there was a change in vibration signal. Then, the process was carried out by varying machining parameters and the corresponding vibration signals were recorded in the system.

### IV. FEATURE EXTRACTION

From the vibration signals, descriptive statistical parameters such as mean, median, mode, kurtosis, skewness, standard error, standard deviation, minimum, maximum, sum, and range are computed to serve as features. They are named as ‘statistical features’ here. Brief descriptions about the extracted features are given below.
(g) Minimum Value: It refers to the minimum signal point value in a given signal. As the bearing parts (inner race, outer race) get degraded, the vibration levels seem to go high. Therefore, it can be used to detect faulty bearing condition.

(h) Maximum Value: It refers to the maximum signal point value in a given signal.

(i) Sum: It is the sum of all feature values for each sample.

V. GAUSSIAN PROCESS

Regression is often formulated as the task of predicting the scalar output $y^*$ associated to the $D$-dimensional input $x^*$, given a training data set $D \equiv \{x_j, y_j\}_{j=1}^{n}$ of $n$ input-output pairs. A common approach is to assume that the outputs have been generated by an unknown latent function $f(x)$ and independently corrupted by additive Gaussian noise of constant variance $\sigma_n^2$:

$$y_j = f(x_j) + \epsilon_j, \quad \epsilon_j \sim N(0, \sigma_n^2)$$

The regression task boils down to making inference about $f(x)$. Gaussian process (GP) regression is a probabilistic, non-parametric Bayesian approach. A Gaussian process prior distribution on $f(x)$ allows us to encode assumptions about the smoothness (or other properties) of the latent function. For any set of inputs $\{x_j\}_{j=1}^{n}$ the corresponding vector of function evaluations $f = \{f(x_1), \ldots, f(x_n)\}^T$ has a joint Gaussian distribution:

$$p(f|\{x_1\}^{n}_{n=1}) = N(f|0, K_{ff}).$$

The following common practice of setting the mean of the process to zero. The properties of the GP prior over functions are governed by the covariance function

$$K_{ff}(i, j) = k(x_i, x_j) = E[f(x_i)f(x_j)],$$

which determines how the similarity between a pair of function values varies as a function of the corresponding pair of inputs. A covariance function is stationary if it only depends on the differences between its inputs $k(x_i, x_j) = k(x_i - x_j) = k(\tau)$

The elegance of the GP framework is that the properties of the function are conveniently expressed directly in terms of the covariance function, rather than implicitly via basis functions.

To obtain the predictive distribution $p(y^*|x^*,D)$ it is useful to express the model in matrix notation by stacking the targets $y_j$ in vector $y = [y_1, \ldots, y_n]^T$ and writing the joint distribution of training and test targets:

$$\begin{bmatrix} y \\ y^* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K_{yy} + \sigma_n^2 I_n & K_{yf^*} \\ K_{f^*y} & K_{f^*f^*} + \sigma_n^2 I_n \end{bmatrix}\right)$$

where $K_{yy}$ is the vector of covariances between $f(x)$ and the training latent function values, and $K_{f^*f^*}$ is the prior variance of $f(x)$. $I_n$ is the $n \times n$ identity. The predictive distribution is obtained by conditioning on the observed training outputs:

$$\begin{align*}
p(y|x, D) &= N(\mu, \sigma^2) \\
\text{where} \quad \mu &= K_{yf^*}(K_{ff} + \sigma_n^2 I_n)^{-1} y \\
\sigma^2 &= (\sigma_n^2 + K_{f^*f^*} - (K_{ff} + \sigma_n^2 I_n)^{-1} K_{f^*})
\end{align*}$$

The covariance function is parameterized by hyperparameters. This covariance function is also known as the ARD (Automatic Relevance Determination) squared exponential, because it can effectively prune input dimensions by growing the corresponding length scales. It is convenient to denote all hyperparameters including the noise variance by q. These can be learned by maximizing the evidence, or log marginal likelihood:

$$\log p(y|\theta) = -\frac{n}{2} \log(2\pi) - \frac{1}{2} y^T(K_{ff} + \sigma_n^2 I_n)^{-1} y - \frac{1}{2} \log |K_{ff} + \sigma_n^2 I_n|$$

Provided there exist analytic forms for the gradients of the covariance function with respect to the hyperparameters, the evidence can be maximized by using a gradient-based search. Unfortunately, computing the evidence and the gradients requires the inversion of the covariance matrix $K_{ff} + \sigma_n^2 I_n$ at a cost of $O(n^3)$ operations, which is prohibitive for large data sets.

VI. RESULTS AND DISCUSSION

After completing the experiment, the data were stored in the computer. From the data, statistical futures were extracted using the Microsoft Excel software. The regression analysis using Gaussian process was made by the weka software. The developed regression model equation using Gaussian process is shown in Table 3.

<table>
<thead>
<tr>
<th>Table 3. Gaussian Regression Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kernel used: RBF kernel: $K(x,y) = e^{-((x-y,x-y)^2)}$</td>
</tr>
<tr>
<td>Average Target Value: 2.1674</td>
</tr>
<tr>
<td>Inverted Covariance Matrix:</td>
</tr>
<tr>
<td>Lowest Value = -0.1402</td>
</tr>
<tr>
<td>Highest Value = 0.9757</td>
</tr>
<tr>
<td>Inverted Covariance Matrix * Target-value Vector:</td>
</tr>
<tr>
<td>Lowest Value = -0.1591</td>
</tr>
<tr>
<td>Highest Value = 0.1647</td>
</tr>
</tbody>
</table>

The correlation coefficient gives information about how well the regression model fits the experimental data. If the correlation coefficient value is close to ‘one’, then the model best fits the data and the prediction value is expected to be close to the actual data. Referring to Table 3, the regression model built in this study is expected to give better surface roughness prediction results for all cutting conditions considered in this study.
It is evident from Table 4 that for these conditions, the surface roughness predicted by Gaussian model is expected to be closer to the actual experimental data. It is confirmed by lower values of percentage of mean absolute error. This result is further reinforced by corresponding other error measures such as Root mean squared error (%), Relative absolute error (%) and Root relative squared error (%) as shown in Table 4.

If one assumes that the data acquisition is done with all care and free from errors, then next possibility to improve the regression model accuracy is by building separate regressive model for each speed.

VII. CONCLUSION

The objective of this study is to develop the best suitable model in predicting surface roughness in boring process. The experimental data of measured surface roughness was utilized to develop model. The developed Gaussian model was used in predicting surface roughness for various cutting conditions with tool post vibration signal. The developed prediction system was found to be capable of accurate surface roughness prediction. All data, experimentally obtained and collected from previous studies, have been used to develop the models based on prediction accuracy and can be extended to testing relative biases, ability to extrapolate and others.

REFERENCES


