Recognizing Surface Roughness to Enhance Milling Operations

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Metal cutting is one of the most significant manufacturing processes in the area of material removal (Chen & Smith, 1997). Black (1979) defined metal cutting as the removal of metal chips from a workpiece in order to obtain a finished product with desired attributes of size, shape, and surface roughness. Drilling, sawing, turning, and milling are some of the processes used to remove material to produce specific, high-quality products.

The quality of machined components is evaluated by how closely they adhere to set product specifications of length, width, diameter, surface finish, and reflective properties. In high-speed turning operations, dimensional accuracy, tool wear, and quality of surface finish are three factors that manufacturers must be able to control (Lahidji, 1997). Among various process conditions, surface finish is central to determining the quality of a workpiece (Coker & Shin, 1996). Attaining and tracking a desired surface roughness is more difficult than producing physical dimensions because relatively more factors affect surface roughness. Some of these factors can be controlled and some cannot. Controllable process parameters include feed, cutting speed, tool geometry, and tool setup. Factors that cannot be controlled as easily include tool, workpiece, and machine vibration; tool wear and degradation; and workpiece and tool material variability (Coker & Shin, 1996).

Techniques of Surface Roughness Measurement

Surface measurement techniques are grouped into contact and noncontact methods. An amplified stylus profilometer is the most popular and prevalent contact instrument used to measure surface roughness in industry and research laboratories because it is fast, repeatable, easy to interpret, and relatively inexpensive (Mitsui, 1986; Shin, Oh, & Coker, 1995). In addition, stylus profilometers are used as the standard for comparing most of the newly invented surface roughness measurement instruments or techniques. This instrument uses a tracer or pickup incorporating a diamond stylus and a transducer. Running the stylus tip across the workpiece surface generates electrical signals corresponding to surface roughness. The electrical signals are amplified, converted from analog to digital, processed according to an algorithm, and displayed. The measurement has a fairly good resolution and a large range that satisfies the measurements of most manufactured surfaces. However, this stylus profilometer is limited because it requires an excessive amount of time to scan large areas, it has a limited range of use on nonflat surfaces, and it is restricted to off-line use (Shin et al., 1995). Off-line and in-process measurements are compared in the next section.

In-Process Versus Off-Line Measurement

Monitoring can be performed in-process or off-line using direct or indirect methods (Cook, 1980). Critical need for in-process tool and process monitoring has developed since computer numerically controlled (CNC) machines and automated machining centers have become more widespread (Koren, 1989). Monitoring individual machining processes in real time is critical to integrating those processes into the overall machining system. The in-process designation for a sensing method means that it is performed while metal is being removed (or during normal disengagement) without interrupting the process.

Off-line methods can be performed on the machine or away from the machine. In either case, off-line methods require either scheduling idle time or interrupting the process for measurement. In-process and off-line methods are effective in gathering important information about surface characteristics, but in-process methods are preferred. In-process monitoring provides real-time information concerning the machining process. This real-time feedback enables the machinist or operator to adjust the appropriate machining parameters in order to produce the desired surface roughness, reduce tool wear, and/or reduce the probability of tool breakage. However, monitoring or measurement conducted in-process or off-line would not be possible without the use of sensory devices.

Sensor technology is playing an ever-increasing role in the manufacturing environment for a wide variety of tasks, such as tool wear assessment, machine tool condition monitoring, and quantification of the surface finish. The demand for incorporating sensor technology into the production environment is being driven by increasing need to minimize manufacturing costs while simultaneously producing higher quality products.

Sensor technology can measure surface characteristics either directly or indirectly. Direct measurement methods using sensors include optical, electromagnetic, and ultrasonic methods. Direct sensors scan the workpiece surface directly and obtain surface roughness information as well as workpiece dimensions. However, these processes are limited because the presence of chips and/or cutting fluid blocks the line of sight they require to measure the workpiece surface. Indirect methods have been successfully used (Tsai, Chen, & Lou, 1999) to extrapolate the surface condition from vibration signals measured by the accelerometer or dynamometer. Indirect measurement is not impeded by the presence of chips and cutting, and thus is a more robust measurement method. For that reason, the present research employs an accelerometer sensor to indirectly measure surface roughness in real time.

Purpose of the Study

The purpose of this research was to develop a multilevel, in-process surface roughness recognition (M-ISRR) system to evaluate surface roughness in process and in real time. To develop this system precisely, the following key factors related to surface roughness during the machining process had to be identified: feed rate, spindle speed, depth of cut of the process, tool and workpiece materials, and so on. In addition, the dynamics of the machining process generate vibration between the tool and workpiece while the machining process is taking place. Vibration information was a key factor in the development of the M-ISRR system.

Research by Lou and Chen (1997) involving an in-process surface recognition (ISR) system resulted in the successful development of a surface recognition system. Their study attained approximately 93% accuracy with only one tool type and one work material. The M-ISRR system in the present research extends Lou and Chen's findings by using multiple tools and work materials. The present M-ISRR system provides a more robust R_a prediction system by incorporating multiple work materials, tools, and setup parameters. This system will provide the real-time surface roughness (R_a) values needed for in-process decision making in a more realistic industrial environment. A multiple regression analysis approach was used to develop the M-ISRR system.

Experimental Setup and Signal Processing

In any study, equipment and hardware play critical roles in conducting a viable experiment and collecting results consistent with the purpose of the study. A fundamental understanding of computer/machining equipment and data acquisition devices, which include proximity sensors, accelerometers, and signal converters (i.e., analog to digital or digital to analog), is important in understanding the activities conducted in this research. Accordingly, hardware and software used in this research are discussed in the next two sections.

Hardware Setup

All machining was done in a Fadal VMC (vertical machining center) with multiple tool-change capability. This machine is capable of three-axis movement (along the *x, y,* and *z* planes). Programs can be developed in the VMC directly or downloaded from a 3.5" diskette or data link. Information was collected using a 353B33 accelerometer and a Micro Switch 922 Series 3-wire DC proximity sensor. The accelerometer was used to collect vibration data generated by the cutting action of the work tool. The proximity sensor was used to count the rotations of the spindle as the tool was cutting. The proximity information then was graphed along with the accelerometer data, which enabled the identification of vibrations produced during different phases of the cutting sequence. Data from both sensors were converted from analog to digital signals through an Omega CIO-DAS-1602/12 A/D converter. The A/D converter-output was connected to a Pentium I personal computer via an I/O interface (see Figure 1).

Two power supplies were used. One power supply was used to amplify the signal from the accelerometer. This amplified signal was then sent to the A/D board. The second power supply was used to power the proximity sensor and circuitry. A signal was produced during the switched phase of the proximity sensor.

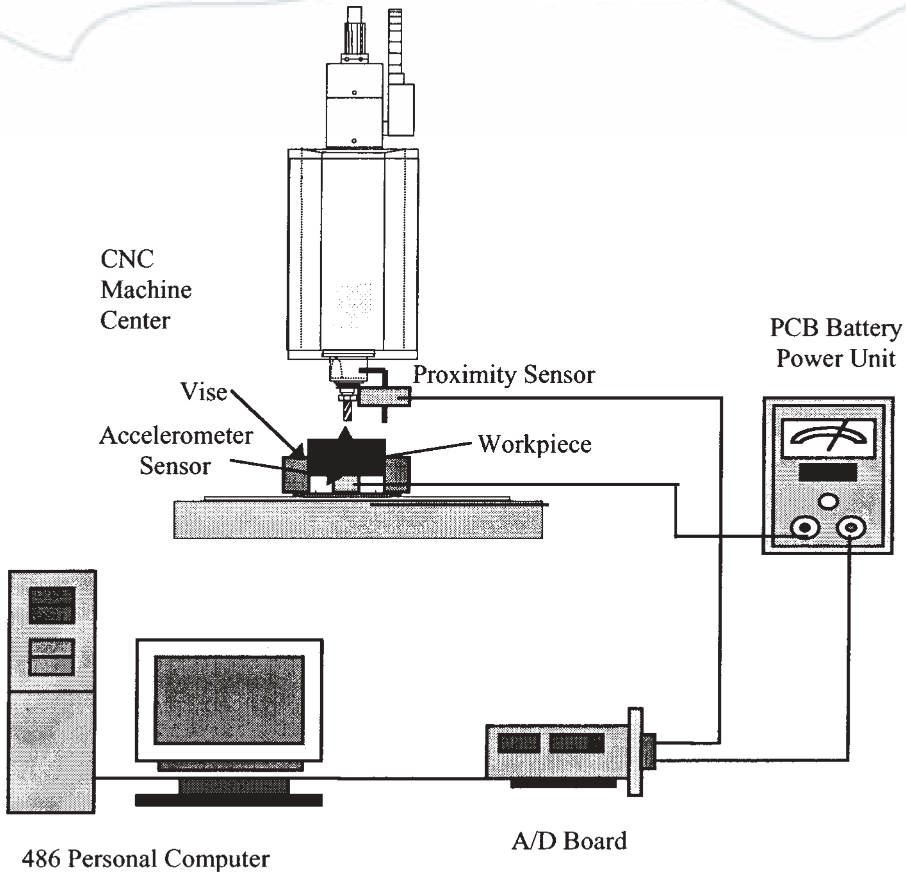

Figure 1. Experimental setup.

This signal was sent to the A/D board on a separate channel from the one used for the accelerometer signal.

The workpiece material used in this research was 6061 aluminum and 1018 steel blocks. The blocks were cut 1.00" x 1.00" x 1.00". Various feed and spindle speeds, depths of cut, work materials, tool materials and types, and tool diameters were tested.

The Federal PocketSurf stylus profilometer was used off-line to measure the surface roughness value of the machined samples. The surface finish measurements were made off-line with the roughness average R_a values rated in microinches (μi).

Software Setup

The software setup consisted of a CNC machining program, an A/D converting program, and a rotational average calculation program. The CNC machining program was written for cutting the workpieces at different spindle speeds, feed rates, and depths of cut. The A/D converting program was developed in C programming language. The rotational average calculation program calculated the vibration average per revolution. The Statistical Package for the Social Sciences (SPSS) version 8.0 software was used for computation and in the development of the multiple regression model.

Experimental Design of MR-M-ISRR

The multiple regression model contained seven independent variables. The seven independent variables were comprised of three categorical parameters and four interval parameters. The four interval parameters were (*F*) feed rate (X_{1i}), (*D*) depth of cut (X_{2i}), (*S*) spindle speed (X_{3i}), and (*V*) vibration average per revolution (X_{4i}) of the accelerometer sensor. The three categorical parameters were (*TD*) tool diameter (CX_{1i}), (*TM*) tool material (CX_{2i}), and (*WM*) work material (CX_{3i}). The regression equation for each design did not include *TD, TM,* or *WM*. These were categorical variables and could not be used as predictors.

The vibration average per revolution from the accelerometer was collected and converted to digital data through the A/D converter and stored. Figure 2 displays an example of the proximity and accelerometer data collected with a 1.00" cutting tool at a feed rate of

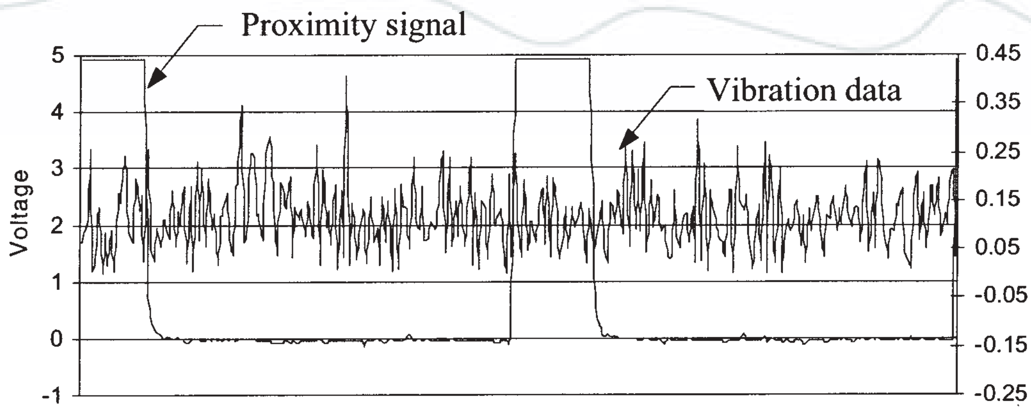

Figure 2. Sample vibration and proximity signal.

20 ipm. The following equation indicates the method of calculating the five average vibration data:

$$V_i = \sum_{j=(i-1)*k}^{i*k} |Vibration(j)|/k,\ i=1,2,3,4, and\ 5$$

where k represents the total number of data in each revolution, as indicated in Figure 2. For example, if $i = 1$, then the V_i was calculated through the vibration data points from point number 0 to point number k (to have a total of k data in one revolution). Vibration (V_i) was measured in units of voltage.

Four steps were used in developing the regression model:

1. Determine the regression model (Kirk, 1995):
   $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_{h-1} X_{i,h-1} + \varepsilon_i \ (i, \ldots, N)$
   where Y_i=the predicted R_a value, $\beta_0, \ldots, \beta_{h-1}$ are the partial regression coefficients, $X_{i1}, \ldots, X_{i,hi}$ are the independent variables, and ε_i is the random error term with mean equal to zero and variance equal to σ^2_ε
2. Determine R, R^2, Adjusted R^2. The multiple correlation coefficient R is a Pearson product-moment correlation coefficient between the criterion variable Y and the predicted score on the criterion variable, $\hat{Y}$. R can be expressed as:

   $$R_{Y\cdot 1,2 \ldots K} = \sqrt{\beta_1 r_{Y1} + \beta_2 r_{Y2} + \ldots + \beta_K r_{YK}} = R_{y\hat{y}}$$

   The proportion of the variation in the criterion variable that can be attributed to the variation of the combined predictor variables is represented by the square of the multiple correlation coefficient, or R^2.
3. Determine whether the value of multiple R is statistically significant. For multiple correlation, one can test the null hypothesis H_o: $R = 0$. An F statistic can be used to test this hypothesis by the following :

   $$F = \frac{R^2 / k^2}{(1 - R^2)/(n - k - 1)}$$

   where R = the multiple correlation coefficient and k = the number of predictor variables. If the computed value of F exceeds the critical value of F for a given level of significance, then H_o: $R = 0$ is rejected.
4. Determine the significance of the predictor variables. The regression coefficient can be tested for statistical significance by the value:

   $$t = \frac{\beta_i}{S_{\beta i}}$$

   where β_i = the regression coefficient and $S_{\beta i}$ = the standard error of the respective coefficient.

In this proposed model, the dependent variable was the surface roughness average value, R_a (Y_i). The structure of the multiple-regression, multilevel in-process surface roughness recognition (MR-M-ISRR) model is depicted in Figure 3. The proposed multiple-regression model was a two-way interaction equation:

$$\begin{aligned} Y_i = {} & \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} \\ & + \beta_5 X_{1i} X_{2i} + \beta_6 X_{1i} X_{3i} + \beta_7 X_{1i} X_{4i} \\ & + \beta_8 X_{2i} X_{3i} + \beta_9 X_{2i} X_{4i} + \beta_{10} X_{3i} X_{4i} + \varepsilon_i \end{aligned}$$

Three methods were used in developing

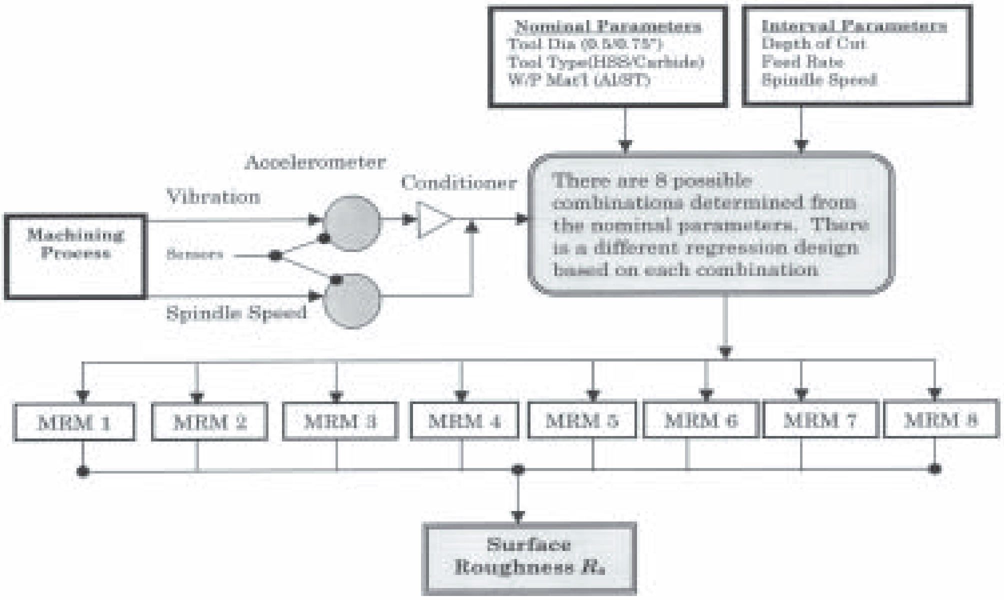

Figure 3. The structure of the MR-M-ISRR model.

the multiple-regression equations. First was the enter method, which entered all independent variables into the regression model regardless of the their significance. Second was the forward method, which entered the independent variables one at a time based on their significance. This method was built using only significant independent variables. Third, the forward method was used again except that the dependent variable R_a was transformed with the natural log function (e^x). This method was used to smooth the dispersion of the R_a values.

Analysis and Results

Eight multiple-regression equations were developed from the training data collected. A total of 384 experimental runs were carried out in order to develop the regression equation for the eight designs. Table 1 shows the parameters and settings of samples collected for developing the multiple-regression equations for each design. Within these experimental runs, some data were used for testing as well. In addition to these experimental runs, a total of 64 runs (as shown in Table 2) were performed to gather testing data for evaluating the accuracy of the proposed model. From each sample, five R_a readings were taken with the profilometer and five (V_i) averages were collected. The two-way interaction equation was used for each design in order to develop the best-fit model for surface roughness recognition.

The accuracy of the proposed MR-M-ISRR system was determined by calculating the deviation of the proposed regression model

Table 1. Parameters and Settings for the Training Data

Feed (ipm)	Depth (inches)	Rpm
8	0.01	1500
11	0.02	1667
14	0.03	1833
16		2000

Table 2. Parameters and Settings for the Testing Data

Feed (ipm)	Depth (inches)	Rpm
10	0.015	1583
14	0.025	1917

Table 3. Multiple Regression Equations for Design (*j*)

Design (*j*)	Regression Equation
1	$Ra_1 = -48.674 + 6.034X_{11} + 1390.841X_{12} + 0.03027X_{13} - 197.771X_{14} - 0.002765X_{11}X_{13} - 0.969X_{12}X_{13} + 0.08889X_{13}X_{14} + 33.483X_{11}X_{13} + 0.704X_{12}X_{13}X_{14}$.
2	$Ra_2 = 77.896 + 12.232X_{21} - 3660.757X_{22} - 0.0572X_{23} - 2680.321X_{24} - 0.003425X_{21}X_{23} + 3.747X_{22}X_{23} + 2.164X_{23}X_{24} - 93.377X_{21}X_{22} - 91.797X_{22}X_{23}X_{24} + 117816.740X_{22}X_{24}$.
3	$Ra_3 = 3.927 + 0.04071X_{31} - 0.0001686X_{33} + 144.76X_{32}X_{34}$.
4	$Ra_4 = e^{**}(-6.618 + 0.162{*}X_{41} + 573.629X_{42} + 0.005809X_{43} + 271.141X_{44} - 0.00003366X_{41}X_{43} - 0.34X_{42}X_{43} - 0.149X_{43}X_{44} - 14249.05X_{42}X_{44} - 1.801X_{41}X_{44} + 8.248X_{42}X_{43}X_{44})$.
5	$Ra_5 = 53.837 - 0.437X_{51} - 1878.232X_{52} - 0.02558X_{53} -204.241X_{54} + 0.0006958X_{51}X_{53} + 0.961X_{52}X_{53} + 0.144X_{53}X_{54} + 3.681X_{51}X_{52} + 18430.247X_{52}X_{54} - 5.646X_{51}X_{54} - 9.806X_{52}X_{53}X_{54}$.
6	$Ra_6 = e^{**}(4.48 + 0.0004797X_3 - 0.00004858X_1X_3 + 0.0106X_2X_3 - 0.009122X_3X_4 - 4.378X_1X_2 + 547.698X_2X_4 + 1.627X_1X_4 - 0.209X_2X_3X_4)$.
7	$Ra_7 = 21.399 + 2.078X_{71} + 719.455X_{72} + 0.0004339X_{73} + 562.564X_{74} + 0.00001519X_{71}X_{73} - 0.295X_{72}X_{73} - 0.05761X_{73}X_{74} - 0.146X_{71}X_{72} + 1775.765X_{72}X_{74} - 29.665X_{71}X_{74} - 2.835X_{72}X_{73}X_{74}$.
8	$Ra_8 = -48.567+5.364X_{81} + 7684.154X_{82} - 233.178X_{84} - 0.494X_{82}X_{83} + 0.828X_{83}X_{84} - 348.446X_{81}X_{82} - 29.838X_{82}X_{83}X_{84}$

(Ra'_{ij}) from the actual profilometer measurement (Ra_{ij}) taken from each sample. The deviation for each testing sample under design *j* was denoted by $\forall_{kj}$ and was defined as follows:

$$ø_{kj} = \frac{|Ra_{ij} - Ra'_{ij}|}{Ra_{ij}}$$

After the deviation of each testing sample under design *j* was determined, the average deviation of each design (*j*) was calculated as follows:

$$\bar{ø}_j = \frac{\sum_{k=1}^{m} ø_{kj}}{m}$$

where m = number of samples with each design (in this case, m = 8). After the deviation of each design was calculated, the overall average for the MR-M-ISRR system was defined as follows:

$$\bar{\bar{ø}} = \frac{\sum_{j=1}^{n} \bar{ø}_j}{n}$$

where n is the number of designs (in this case, n = 8).

Results and Summary

Eight multiple regression designs were developed successfully with the resultant equations displayed in Table 3. The recognition accuracy of this proposed MR-M-ISRR system is summarized in Table 4. Designs 2 and 7, both using the forward method, resulted in the least deviation from the actual R_a value. Design 4 had the third least deviation from the R_a value. The method used for Design 4 was the forward method with R_a transformed.

The overall MR-M-ISRR system demonstrated 82% accuracy of prediction average, establishing a promising step to further development in in-process surface roughness recognition systems. In consideration of the MR-M-ISRR systems' less-than-exceptional recognition accuracy, this research does support the use of regression analysis techniques to model dynamic machining processes. Improved accuracy utilizing regression analysis techniques is achievable but will require a dramatic increase in experimental sample sizes involving the use of multiple tools and materials. Furthermore, an alternative method for developing an in-process prediction system should be considered. Alternative methods demonstrating learning capability within the prediction system are most desirable. The use

Table 4. The Overall Accuracy for the MR-M-ISRR System Using the Testing Data Sets

Design (j)	Design Configuration	Average Deviation for MR Model	Samples (m)
1	$TD_1TM_1WM_1$	.0906	8
2	$TD_1TM_1WM_2$	.1211	8
3	$TD_1TM_2WM_1$	.2748	8
4	$TD_1TM_2WM_2$	.2200	8
5	$TD_2TM_1WM_1$	.0482	8
6	$TD_2TM_1WM_2$	.2586	8
7	$TD_2TM_2WM_1$	.1006	8
8	$TD_2TM_2WM_2$	.3497	8
Total $n = 8$		18.3%	64
Accuracy		82%	

of neural network algorithms or fuzzy net methodologies provides feasible alternatives for surface roughness recognition model development. In the development of an ISRR system, similar research utilizing neural networks and fuzzy nets has demonstrated commendable results. Therefore, continued research focused in ISRR system development is promising.

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