An In-Process Surface Roughness Recognition System in End Milling Operations

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Computer numerical control (CNC) machines have been very successful in increasing productivity, repeatability, and accuracy of parts, reducing production and labor costs, and lowering operator skill in manufacturing industry (Degarmo, Black, & Kohser, 1999). In order to assure machined part quality, the operator traditionally inspects the machined parts by stopping the machine, cleaning the workpiece, and removing the workpiece from the machine table. Then, the inspection instruments are able to measure quality characteristics, such as surface roughness, inspected by a stylus profilometer. It is very time and cost consuming to conduct a quality inspection of machined parts in this manner. If there were an in-process inspection technique that could be used to measure quality characteristics of machined parts in a real-time manner without stopping the machine and removing the workpiece, productivity could be increased and time and money could be saved.

To develop an in-process quality control system, a sensor technique and a decision-making algorithm need to be applied during machining operations. Several sensor techniques have been used in the in-process prediction of quality characteristics in machining operations. For example, an accelerometer sensor was used to monitor the vibration of milling operations to develop an on-line surface roughness measuring technique in end milling operations (Chen & Lou, 1999; Jang, Choi, Kim, & Hsiao, 1996). An ultrasonic sensor was used to develop an in-process measurement of ultrasonic beams from surface roughness in milling operations (Coker & Shin, 1996). An acoustic emission sensor was used to monitor transient stress waves to estimate surface roughness in grinding (Susic & Grabec, 1995). A dynamometer sensor can be used to generate cutting forces in machining; however, the effects of surface roughness caused by cutting forces have not been taken into consideration in past research. Lee and Lin (2000) indicated that cutting forces have the most significant impact on the quality of machined parts in end milling operations. Therefore, cutting force is to be included in developing cutting parameters affecting a surface roughness recognition system in end milling operations.

After a sensor has been selected to monitor machining operations, a proper decision-making algorithm needs to be developed to establish a recognition system by using the data collected from the sensor. Many decision-making algorithms have been developed throughout the past decade. For example, fuzzy logic, neural network, and neural fuzzy systems have been applied in the in-process surface roughness recognition (IPSRR) system (Chen & Savage, 2001; Coker & Shin, 1996; Chen & Lou, 1999, 2000; Susic & Grabec, 1995; Tsai, Chen, & Lou, 1999). Recently, a statistical approach has been effectively used for prediction, process optimization, and process control in manufacturing areas (Montgomery, 1997). For example, Fuh and Wu (1995) and Chen and Lou (1999) proposed a statistical model for surface quality prediction in end milling operations.

In this research, a multiple linear regression (MLR)-based IPSRR system using a dynamometer was applied to predict surface roughness using cutting force, spindle speed, feed rate, and depth of cut as input parameters in end milling operations.

What We Did

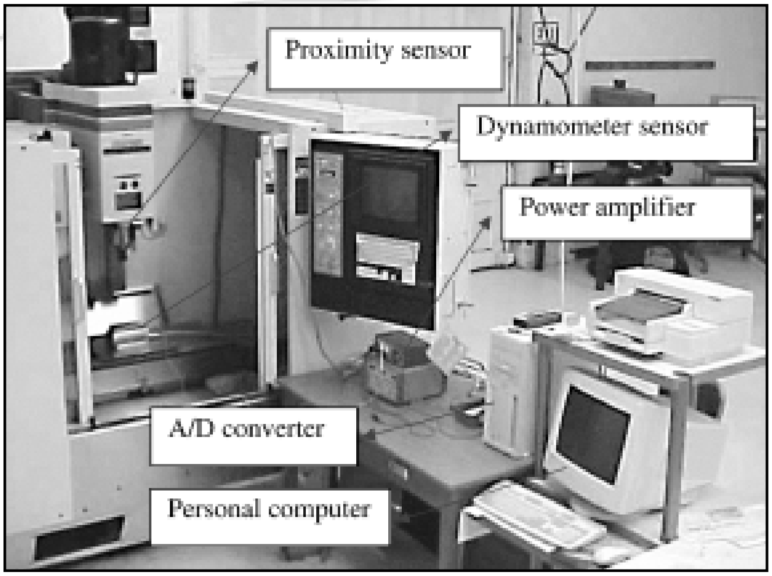
An MLR-IPSRR system was developed and implemented in two steps:

1. The magnitude of the cutting force in the end milling operation that had the highest correlation for predicting surface roughness of the finished parts was identified.
2. The MLR-IPSRR system, including the above-mentioned cutting force and cutting parameters, was developed and tested.

Procedure

Figure 1 illustrates the experimental setup consisting of the hardware and software used to accomplish the two steps.

Figure 1. Experimental setup for the proposed MLR-IPSRR system.



The hardware included:

- A Fadal vertical CNC milling machine with multiple tool changing and a 15 HP spindle.
- A Kistler 9257B type dynamometer sensor, which provided dynamic measurement of the three orthogonal components of a force signal (F_x, F_y, and F_z).
- A Micro Switch 922 series 3-wire DC proximity sensor, used to collect the signal for counting the rotations of the spindle as the tool was cutting.
- A power supplier, used to amplify the signals from the proximity and the dynamometer sensors. This amplified signal was then sent to the A/D board.
- An omega CIO-DAS-1602/12 A/D converter, used to convert both the dynamometer and proximity sensor data from analog to digital signals.
- A P5 133 personal computer, which was connected to collect data from the A/D converter output via an I/O interface.
- A 6061 aluminum workpiece with dimensions of 1.00" x 1 .00" x 1.00", which was cut in the end milling operations.

In order to control end milling operations and analyze the spindle revolution and cutting force signals, the following software was required: (a) Basic CNC codes, which were applied to conduct cutting operations, and (b) A/D converter software, which was used to convert data (proximity and cutting forces) from analog signals to digital values. Using the hardware and software setups, tests of cut were performed. Figure 2 shows the data obtained from this experimental run using spindle speed (S = 2500 rpm), feed rate (F = 8 ipm), and depth of cut (D = 0.08 in.).

The Cutting Forces Analysis

From Figure 2, the cutting force data were collected from the dynamometer sensor; these three forces (F_x, F_y, and F_z) cannot individually represent the actual force affecting surface rough-

Figure 2. Proximity and cutting force digital data using cutting condition S = 2500 rpm, F = 8 ipm, and D = 0.08 in.

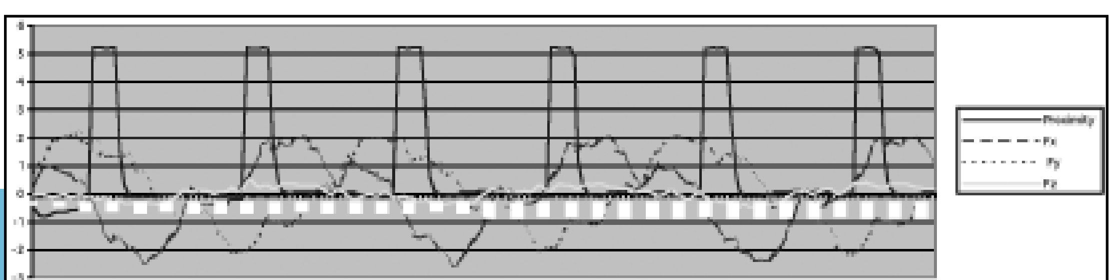
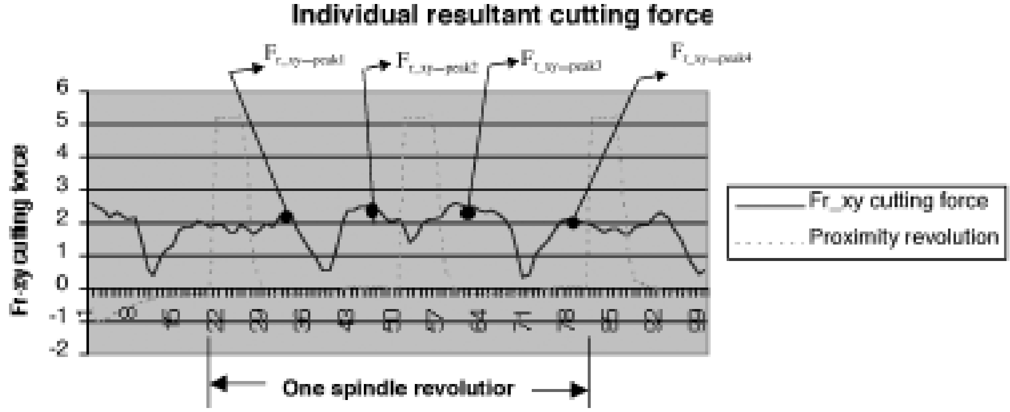


Figure 3. Individual resultant cutting force Fr_xy and four peak forces in one revolution at cutting condition of F = 20 ipm, S = 2000 rpm, D = 0.08 in.



ness. Four cutting force magnitudes ($\overline{F}_{r\_xy}$, $\overline{F}_{r\_xy\_peak}$, $\overline{F}_z$, and $\overline{F}_{r\_xyz}$) were considered as possible candidates for an input factor for the MLR-IPSRR system. They are defined as:

1. Average resultant force of the x and y directions per revolution ($\overline{F}_{r\_xy}$).

By using the following equation, one could find the individual resultant force (F_{r_xy}) from the x and y directions as shown in Figure 3.

$$F_{r\_xy\_i} = \sqrt{F_{x\_i}^2 + F_{y\_i}^2}\ , \quad (1)$$

where i is the data point in one revolution. Then, the average resultant force in one revolution ($\overline{F}_{r\_xy}$) could be given as:

$$\overline{F}_{r\_xy} = \frac{\sum_{i=1}^{m} F_{r\_xy\_i}}{m}\ , \quad (2)$$

where $i = 1, 2, \ldots m$ and m is the total data points in one revolution.

2. Average resultant peak force ($\overline{F}_{r\_xy\_peak}$).

By using the data shown in Figure 3, one could also identify the peak force ($F_{r\_xy\_peak}$) from the average resultant forces of the x and y directions ($\overline{F}_{r\_xy}$) in the cut period of each tooth. Then, the average resultant peak force in each revolution ($\overline{F}_{r\_xy\_peak}$) could be given as:

$$\overline{F}_{r\_xy\_peak} = \frac{\sum_{i=1}^{r} F_{r\_xy\_peak\_i}}{r}\ , \quad (3)$$

where $i = 1, 2, \ldots r$ and r is the number of cutting tool teeth. In this study, $r = 4$.

3. Average z direction cutting force per revolution ($\overline{F}_z$).

The third type of force analyzed in this study was the average cutting force in the z direction per revolution ($\overline{F}_z$) and could be given as:

$$\overline{F}_z = \frac{\sum_{i=1}^{m} F_{z_i}}{m}\ , \quad (4)$$

where $i = 1, 2, \ldots m$ and m is the total data points in one revolution.

4. Average resultant force of x, y, and z directions per revolution ($\overline{F}_{r\_xyz}$).

The researcher also wanted to analyze the average resultant force of the x, y, and z directions in one revolution ($\overline{F}_{r\_xyz}$). The force is given as:

$$F_{r\_xyz\_i} = \sqrt{F_{x\_i}^2 + F_{y\_i}^2 + F_{z\_i}^2}\ , \quad (5)$$

where i is the data point in one revolution. Then, the average resultant force in one revolution ($\overline{F}_{r\_xyz}$) could be given as:

$$\overline{F}_{r\_xyz} = \frac{\sum_{i=1}^{m} F_{r\_xyz\_i}}{m}\ , \quad (6)$$

where i = 1, 2, 3… m and m is the total data points in one revolution.

After the above-mentioned cutting forces were formed, we examined the correlation coefficient between these cutting forces and surface roughness. Equation 7 was used to compute the correlation coefficient between surface roughness (Ra) and the average resultant force of the x and y directions ($\overline{F}_{r\_xy}$).

$$\rho_{Ra-\overline{F}_{r\_xy}} = \frac{\sum_{i=1}^{n}\left(Ra_i - \overline{Ra}\right)\left(F_{r\_xyi} - \overline{F}_{r\_xy}\right)}{\sqrt{\sum_{i=1}^{n}\left(Ra_i - \overline{Ra}\right)\left(F_{r\_xyi} - \overline{F}_{r\_xy}\right)}} \quad , (7)$$

where is the correlation coefficient between the average resultant cutting force ($\rho_{Ra-\overline{F}_{r\_xy}}$) and surface roughness, Rai is the ith surface roughness, $i = 1, 2, \ldots n$ (n is total data sets; here $n = 384$), and is the ith average resultant cutting force of the x and y directions, $i = 1, 2, \ldots n$, (n is total data sets; here $n = 384$).

$$\overline{Ra} = \frac{\sum_{i=1}^{n} Ra_i}{n} \qquad \overline{F}_{r\_xy} = \frac{\sum_{i=1}^{n} \overline{F}_{r-xy}}{n}$$

Similarly, the,, and were calculated. The largest value of correlation coefficients between the above-mentioned cutting forces and surface roughness represented the most significant cutting force, which was then used in the development of the MLR-IPSRR system.

Experimental Design

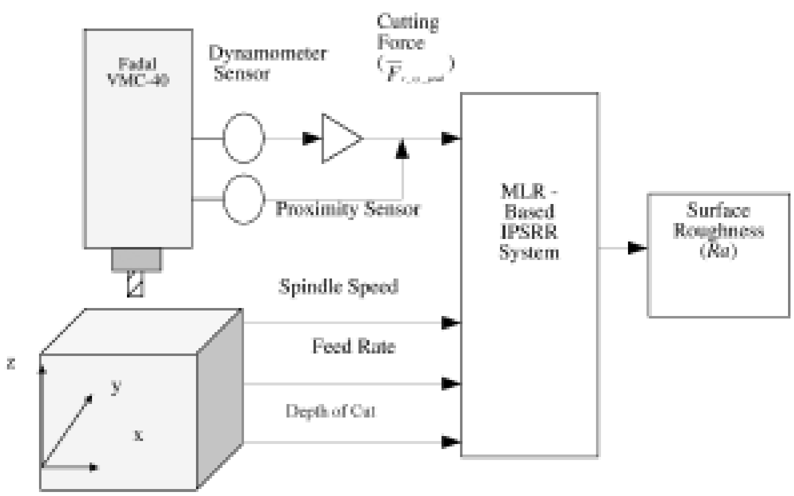
In order to identify the most significant cutting force for the MLR-IPSRR system, an experimental design matrix was used to run and collect the training data. The experimental design matrix, including eight levels of feed rate (6, 8, 10, 12, 14, 16, 18, and 20 ipm), four levels of spindle speed (1750, 2000, 2250, and 2500 rpm), and three levels of depth of cut (0.04, 0.06, and 0.08 in.), was designed for the experiments with two replicates of each experiment. Two end milling tools (1/2 in. with four teeth) were used to cut the workpiece. Therefore, a total of 8*4*3*2*2 = 384 sets of training data were collected. Cutting forces (Fx, Fy, and Fz) were collected using a dynamometer, as shown in Figure 1. The average resultant force of the x and y directions $(\overline{F}_{r\_xy})$, average resultant peak force $(\overline{F}_{r\_xy\_peak})$, average cutting force of the z direction $(\overline{F}_{z})$, and average resultant force of the x, y, and z directions $(\overline{F}_{r\_xyz})$ were calculated using Equations 2, 3, 4, and 5.

The 384 specimens were measured offline with a Pocket Surf stylus type profilometer (produced by Federal Products Co.) to obtain surface roughness (Ra) in this study. A JMP (a product of the SAS Institute) statistical software package was used to calculate the correlation coefficient between surface roughness and cutting forces. The results were $\rho_{Ra-\overline{F}_{r\_xy}} = 0.49$, $\rho_{Ra-\overline{F}_{r\_xy\_peak}} = 0.53$, $\rho_{Ra-\overline{F}_{z}} = 0.46$, and $\rho_{Ra-\overline{F}_{r\_xyz}} = 0.43$; therefore, the average resultant peak force of the x and y directions $(\overline{F}_{r\_xy\_peak})$ had the highest correlation coefficient with surface roughness and was selected as the input parameter for the MLR-IPSRR system.

The Proposed MLR-IPSRR System

After the most significant force was identified, the MLR-IPSRR system shown in Figure 4 was proposed. From Figure 4, one can see the

Figure 4. The structure of the proposed MRL-IPSRR system.



input parameters (average resultant peak force [$\overline{F}_{r\_xy\_peak}$], spindle speed [S], feed rate [F], and depth of cut [D]) and the output parameter (surface roughness [Ra]) used to generate the MLR-IPSRR system. The proposed MLR-IPSRR system is given as:

$$\begin{aligned} Ra_i = {} & \beta_0 + \beta_1 F_i + \beta_2 S_i + \beta_3 D_i + \beta_4 \overline{F}_{r\_xy\_peak} \\ & + \beta_{12} F_i * S_i + \beta_{13} F_i * D_i + \beta_{14} F_i * \overline{F}_{r\_xy\_peak} \\ & + \beta_{23} S_i * D_i + \beta_{24} S_i * \overline{F}_{r\_xy\_peak} \\ & + \beta_{34} D_i * \overline{F}_{r\_xy\_peak} + \beta_{123} F_i * S_i * D_i \\ & + \beta_{124} F_i * S_i * \overline{F}_{r\_xy\_peak} + \beta_{234} S_i * D_i * \overline{F}_{r\_} \\ & + \beta_{1234} F_i * S_i * D_i * \overline{F}_{r\_xy\_peak} + \varepsilon_i \end{aligned}$$

where are coefficients of the regression model, Ra_i is the surface roughness, F_i is the feed rate, S_i is the spindle speed, D_i is the depth of cut, $\overline{F}_{r\_xy\_peak}$ is the average resultant peak force of the x and y directions, and εi ~ N(0, σ2), where i is the number of data sets. To obtain data for the development of a multiple regression prediction model, a total of 384 experimental runs have taken place using the cutting combination indicted in the experimental design section. Therefore, in this study, i = 1, 2, 3,°K384.

Analysis and Results of the System

After utilizing the JMP software package, the results of the surface roughness MLR model were generated as follows:

Ra $_{(predicted)}$ = 57.066-0.024*S + 4.142*F - 0.001*(S - 2125)*(F-13) + 491.056*D + 0.630*(S - 2125)*(D - 0.06) + 41.820*(F - 13)*(D - 0.06) - 0.351* $\overline{F}_{r\_xy\_peak}$ -0.0007*(S - 2125)*($\overline{F}_{r\_xy\_peak}$ - 75.787) + 0.015*(F - 13)*($\overline{F}_{r\_xy\_peak}$ - 75.787) - 0.326*(D - 0.06)*($\overline{F}_{r\_xy\_peak}$ - 5.787) + 0.099*(S - 2125)*(F - 13)*(D - 0.06) - 0.0001*(S - 2125)*(F - 13)*($\overline{F}_{r\_xy\_peak}$ - 75.787) + 0.01*(S - 2125)*(D - 0.06)*($\overline{F}_{r\_xy\_peak}$ - 5.787) + 0.722*(F - 13)*(D - 0.06)* ($\overline{F}_{r\_xy\_peak}$ - 75.787) -0.0016*(S - 2125)*(F - 13)*(D - 0.06)*(- $\overline{F}_{r\_xy\_peak}$ 75.787)

The effect of tests showed that the feed rate, spindle speed, average resultant peak force, and depth of cut influenced the surface roughness significantly since the p values of each main effect (feed rate, spindle speed, average resultant peak force, and depth of cut) were less than a = 0.01 significant level). That is, the surface roughness was mainly determined by the feed rate, spindle speed, average resultant peak force, and depth of cut in end milling operations. The MLR model was also significant with the p value less than a = 0.01. Therefore, the MLR model can be effectively used in this research.

Once the MLR model had been established, the MLR recognition model was tested using 20 sets of cutting conditions that were different from the cutting conditions of experimental designs. The MLR-IPSRR model was implemented in the prediction of the surface roughness while the machining process was taking place. The results of the predicted surface roughness (Ra_i^{MR}) were compared with the finished parts (Ra_{i-m}) that were measured by using a Pocket Surf portable surface roughness gauge. Then, the individual precision $\__i^{MLR}$ of each experimental run (i) was evaluated based on the following equations.

$$\Phi_i^{MLR} = 1 - \frac{Ra_i^{MLR} - Ra_{i-m}}{Ra_i} \tag{8}$$

$$\overline{\Phi}^{MLR} = \frac{\sum_{i=1}^{20} \Phi_i^{MLR}}{20} \tag{9}$$

where Φ_i^{MLR} is the precision of ith testing run, and $\overline{\Phi}^{MLR}$ is the average precision of the 20 testing data, i = 1…20.

The results showed that the capability of the surface roughness prediction was about 86% for the testing experimental data in this study. Therefore, one can see that the surface roughness (Ra) can be predicted effectively by the above-mentioned MLR-IPSRR system.

What We Learned

The purpose of this study was to analyze cutting forces to find out the most significant cutting force magnitude that affected surface roughness and to evaluate whether a MLR approach for surface roughness recognition could be used for prediction in the IPSRR system. Our main conclusions are summarized as follows:

- The average resultant peak force ($\overline{F}_{r\_xy\_peak}$) was identified to be the most significant force to affect surface roughness in this study.

- Spindle speed, feed rate, average peak cutting force, and depth of cut are significant in affecting surface roughness in end milling operations and the determination of the coefficient is R^2 of 0.62 in the MLR model.
- The MLR-IPSRR system is approximately 86% accurate in predicting surface roughness while the machining process is taking place.

This research assumed that the CNC milling machine was effective and stable to conduct all experiments under each cutting condition using an HSS end mill to cut 6061 aluminum material. We believe that the proposed IPSRR system could eventually be implemented in the new age of CNC machines. This would be more likely if additional research and testing could be done such as (a) including different tool material, tool radius, workpiece material, and lubricants in the system and (b) using different methodologies, such as fuzzy logic, neural networks, and fuzzy nets, to provide the IPSRR system with a learning capability. With this capability, the system could be adopted to different machines produced from different CNC manufacturers.

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