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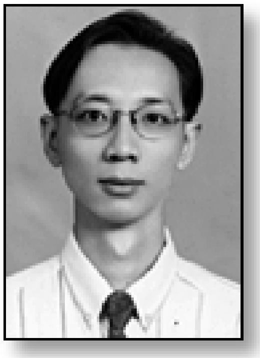

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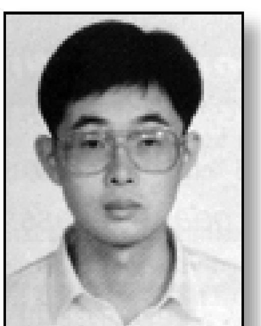

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Introduction

In our fast-paced competitive world, it is very important to recognize the unmanned manufacturing system (UMS) as an essential tool in manufacturing. It can help us to reduce labor cost, to avoid personal oversight, and to enhance the productivity and quality of products. In order to insure efficiency within the system, the provision of monitoring facilities and algorithms for the adaptation of the manufacturing process should be executed accurately (Altintas, Yellowley, and Tlusty, 1988). To perform the UMS effectively in the factory, one important method is to detect the tool breakage automatically, in-process. However, in the actual manufacturing world, most of the computer numerical control (CNC) machines cannot detect the tool conditions in an on-line manner. Because a broken tool may continue functioning without being detected, the materials costs will increase and the quality of products will diminish as errors are made by the broken tool in-process. To reduce the materials costs and prevent damage to the cutting tool, a detecting technology of an unmanned, on-line tool breakage detection system is necessary (Lan and Naerheim, 1986).

However, to be successful in developing a detecting system, it is necessary to implement sensing technology. There are two major approaches using sensing technology for detecting tool breakage: one is the direct method, which measures and evaluates the volumetric change in the tool, and the other is the indirect method, which measures the cutting parameters during the operation process. The indirect method can work as an on-line technique because it measures the cutting parameters during the operation process. To detect the tool breakage immediately, the indirect sensing technology is recommended.

The detection of tool breakage in the milling operations with sensing technology has been widely studied in previous research. Most of the research utilized the principle of vibration and cutting force signals to diagnose the tool condition.

Vibration Signal

The acoustic emission (AE) sensor is used to measure the air vibration created during the cutting process. Principe and Yoon (1991) used the AE sensor and the revolution-oriented processing approach (RORPA) to detect the tool conditions. Vierck and Tlusty (1992) proposed an adaptive threshold by using the AE method to judge the tool condition. Takeshita and Inasaki (1993) used the AE signals to monitor chatter vibration, tool wear and tool breakage. Yan, El-Wardany and Elbestawi (1995) applied the AE method and developed an auto-regressive (AR) model to diagnose the tool breakage.

The accelerometer, which is used to measure surface vibration, is also used to detect the tool condition. W. Chen, C. Chen and Gimmel (in press) developed a Fast-Fourier Transform (FFT) method which transformed the data collected from the accelerometer to judge tool conditions on-line.

Cutting Force Signal

Lan and Naerheim (1986) proposed a time series autoregression (AR) model of force to detect the tool breakage. A time series analysis approach was also applied by Tansel and McLaughlin (1993). Altintas, Yellowley and Tlusty used the method of average force of each peak and difference quasi-mean to generate a model (Altintas, Yellowley and Tlusty, 1988; Altintas and Yellowley, 1989). Tarng and Lee (1993) also developed the average and median force per tooth with a threshold method to judge the tool condition.

The application of neural networks in detecting the tool breakage has been studied in recent years (Ko, Cho and Jung, 1994. Tarng, Hseih and Hwang, 1994). Tansel, Mekdeci and McLaughlin used the Wavelet (1995) Transformations and Neural Networks (WT-NN) to detect the tool failure. A method of telemetering the cutting forces was explained by Deyuan, Yuntai and Dingchang (1995). Chen and Black (1997) designed the Fuzzy-Nets system to distinguish the tool condition.

Purpose of Study

Most of the previous research possesses some disadvantages that are summarized as follows:

1. Some researchers used soft material, like aluminum T6061, which made it difficult for tool breakage to occur.
2. Some researchers used only one broken or one good tool to do the experiment, which is not enough to explain that their particular method can fit other tool breakage situations.

Moreover, the multiple regression model was seldom used to detect the tool conditions. Especially used to build the model with peak force and cutting parameters. Therefore, in this research, multiple tools with the same pattern were selected to cut the hard material in the CNC machine, and a multiple regression model using the cutting parameters was built as a decision-making system to detect the tool breakage on-line.

Methodology

To build a regression model able to detect the tool conditions, the principle of cutting force during the milling process and the theorem of multiple regression must both be understood.

Force of Cutting Process

Milling is an interrupted cutting process. When a tooth enters and leaves the cutting material, it generates a cyclic cutting force from zero to maximum force and returns to zero for each tooth in one direction. The cyclic force looks like a peak. By expanding the principle to the resultant force generated on both x- and y- axes, and the number of peaks in each revolution is found to be equal to the number of teeth found on the milling tool. Therefore, if the tool is in good condition, the peak force of each tooth should be the same for one revolution of the cutting process. Comparatively, if one tooth is broken, the broken tooth will generate a smaller peak force due to a smaller chip load causing the following tooth to obtain a larger peak force than normal. The maximum peak force in each revolution should be different between the good tool and the broken tool, and the maximum peak force of the broken tool should be larger than that of the good tool. Figure 1 shows the difference between cutting patterns of good and broken tools in end milling operation.

Multiple Regression Analysis

Multiple regression is a methodology for studying relationships between variables. It is implemented to determine the relationship between independent and dependent variables and may be used to analyze data and generate a model. From the multiple regression model, one can obtain the predictive variables and determine the relationship between the criterion variable and the predictive variable (Jennrich,1995). Therefore, multiple regression will be useful when predicting the dependent variable such as maximum cutting force of each revolution via independent variables such as spindle speed, feed rate, and depth of cut.

Experiment Design

The objective of the experiment is to detect tool breakage. The following five steps were executed in order to meet the desired objective.

Step 1. Experimental setup

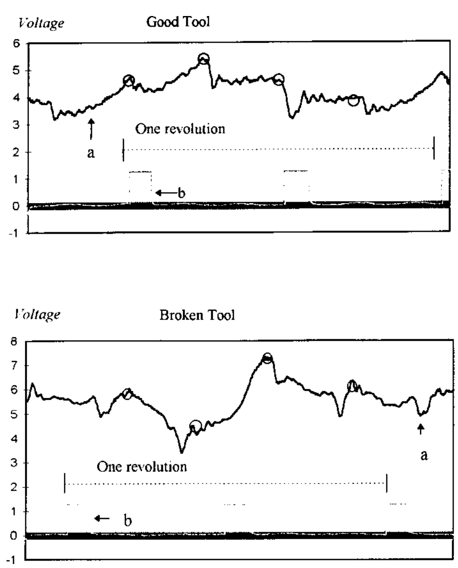
This experiment used a Fadal CNC vertical machining center for test-purposes. A Kistler 9257B 3-component dynamometer was mounted on the table to measure the cutting force, and the steel AISI-1018 (BHN 100) was then mounted on the dynamometer as the workpiece. A proximity sensor was built in near the spindle to confirm the data in each revolution. Four ¾ inch doubt-end four-flute high speed steel cutters were used. In each cutter, one side of the tool was in proper working order and the other side was broken. The broken side of the tool possessed varying degrees of breakage. The experimental setup was shown in Figure 2. The cutting parameters were set as below:

- spindle speed - 450, 500, 550, 600, 650 (rpm)
- feed rate - 10, 12, 15, 18, 20 (ipm)
- depth of cut : 0.06, 0.07, 0.08, 0.09, 0.1 (inch)

Step 2. Data collection

The cutters were selected randomly to execute the experiment. Cutting force was measured in voltage by the Charge Amplifier and transformed to Newtons (N) by the com-

Figure 1. Cutting pattern of good and broken tool



Key	Cutting Parameters
a = force signal	spindle speed = 600 rpm
b = revolution signal	feed rate = 15 ipm
	depth of cut = 0.08 inch

puter. The resultant force, Fr_i, generated from x- and y-axes and the maximum resultant force in each revolution, *Fa*, were used in this experiment. They can be expressed as

$$Fr_i = \sqrt{Fx_i^2 + Fy_i^2} \qquad (1)$$

Where Fx_i: the force in X-direction of point *i* in each revolution

Fy_i: the force in Y-direction of point *i* in each revolution

$$Fa = \max \{ Fr_i \} \qquad (2)$$

The training data were selected randomly within the range of cutting parameters. Each cutting parameter was tested three times with the same tool to build the prediction model. The sample size of training data for the multiple regression model is equal to 105. All the cutting parameters and *Fa* are shown in Table 1.

Step 3. Build the multiple regression model and do the hypotheses test

The multiple regression model of cutting force is a three-way interaction equation:

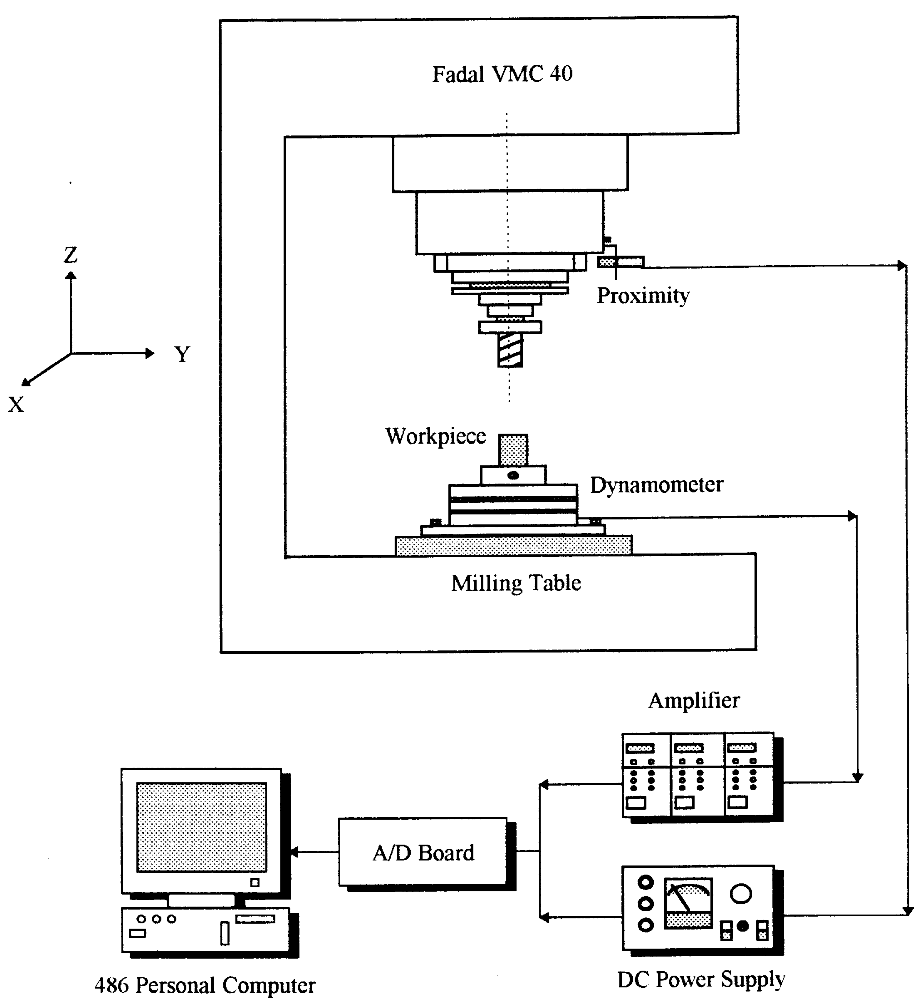
$$yi = ai + b_1x_{1i} + b_2x_{2i} + b_3x_{3i} + b_4x_{1i}x_{2i} + b_5x_{2i}x_{3i} + b_6x_{3i}X_{1i} + b_7x_{1i}x_{2i}x_{3i} \qquad (3)$$

Where *yi*: predictive max. resultant force of each revolution in good tools (N)

$x1i$: spindle speed (rpm)
$x2i$: feed rate (ipm)
$x3i$: depth of cut (inch).

In this model, the dependent variable is the maximum resultant force of each revolution of good tools and the independent variables are spindle speed, feed rate, and depth of cut. Because the independent variables are the controllable cutting parameters of the CNC machine, they can be used to predict the cutting force prior to the cutting process. Through a comparison of the predictive force and the actual force, the tool condition may be detected during the milling process, which could prevent damage to the tool, raw material, and machine.

Figure 2. The experimental setup



The Statistical Analysis System (SAS) was used to build the full regression model listed in equation (1) where the significance level a was set at 0.05 by using the training data. The t-statistic for the null hypotheses (H_o) of each coefficient of variable was necessary to test after we built the model. If the p-value of the coefficient is larger than the significant level, we could say that this variable would accept the null hypotheses and would not affect the dependent variable significantly. Therefore, we should erase the variable and rebuild the regression model until all independent variables accept the alternative hypothesis, H_a. The hypotheses was shown as

$$H_o: b_j = 0 \quad H_a: b_j \neq 0 \quad \text{where } j = 1,2,\ldots,7 \qquad (4)$$

After we deleted the insignificant independent variables, the multiple regression model was built as

$$y_i = 1767.1229 - 1.12368x_{1i} - 94.74684x_{2i} - 14177.31222x_{3i} + 2103.51337x_{2i}x_{3i} \qquad (5)$$

where *yi* represents the predictive maximum resultant force in each revolution, F_p.

The ANOVA table and parameter estimation table were shown in Table 2 and Table 3. From Table 2, because the *F* value of this model is larger than the *F* distribution with 4 and 100 degrees of freedom, the null hypotheses

$$Ho: b_1 = b_2 = b_3 = b_4 = b_5 = 0$$

was rejected. Therefore, at least one of the coefficients in this model are not equal to zero.

Step 4. Calculate the percentage error (e)

Since the actual maximum resultant force in each revolution, *Fa*, was collected by the sensor and the predictive maximum resultant force in each revolution, *Fp*, was measured by the equation (5), we could use the percentage error (e_i) to judge the tool conditions. The percentage error (e_i) was defined as

$$e_i = \frac{|Fa_i - Fp_i|}{Fa_i} \times 100\% \qquad (6)$$

Where Fa_i: actual max. force in each revolution of sample *i*

Fp_i : predictive max. force in each revolution of sample *i*.

Step 5. Set the threshold (l) to detect the tool conditions

An appropriate parameter, l, was selected as a threshold by experience to detect the tool conditions. If e_i is smaller than l, the tool is in a good condition. Otherwise, the tool is broken. In this experiment, the value of l was set at 10% to judge the tool conditions. The method of detecting the tool conditions was defined as

If $e_i < 10\%$, then the tool is in good condition.
If $e_i \geq 10\%$, then the tool is broken.

Results

From this multiple regression model, we find that the feed rate (x_2) and the depth of cut (x_3) have more significant influence on the cutting force than other cutting parameters. The coefficient of determination (R^2) for the regression model in equation (5) is 0.9604 to represent that 96.04% of the total variation can be ascribed to the linear relation.

Since step 2 allows determination of the predictive force, F_p, and the actual force, F_a, and the predictive force, F_p, may be determined by step 3, step 4 can be used to calculate the percentage, and finally, step 5 to detect the tool breakage. Some testing results of using the training data were shown in Table 4. However, these results derive from the same cutting parameters as used for the training. In evaluating the performance of the system, 90 testing data sets using different cutting conditions from the training data are conducted, and the partial results of the testing data are shown in Table 5. From the experimental results, the accuracy of the training data is about 95%, and the accuracy of the testing data is about 91%.

Conclusions

The use of the multiple regression model in detecting the tool breakage is adapted for the resultant cutting forces in end milling operations. This level of accuracy denotes that the regression

Table 1. The Training Data Set

OBS	Force (uN)	Speed (rpm)	Feed (ipm)	Depth (inch)	OBS	Force (uN)	Speed (rpm)	Feed (ipm)	Depth (inch)
1	661.90	450	10	0.06	54	720.74	550	15	0.06
2	644.06	450	10	0.06	55	978.02	550	15	0.07
3	679.28	450	10	0.06	56	951.14	550	15	0.07
4	858.32	450	10	0.08	57	939.54	550	15	0.07
5	870.98	450	10	0.08	58	1191.96	550	15	0.08
6	859.58	450	10	0.08	59	1206.56	550	15	0.08
7	861.96	450	15	0.06	60	1216.90	550	15	0.08
8	851.50	450	15	0.06	61	1367.96	550	15	0.09
9	852.26	450	15	0.06	62	1393.70	550	15	0.09
10	1367.46	450	15	0.08	63	1356.94	550	15	0.09
11	1413.76	450	15	0.08	64	1084.32	550	18	0.07
12	1363.50	450	15	0.08	65	1106.36	550	18	0.07
13	1031.48	450	20	0.06	66	1091.00	550	18	0.07
14	996.80	450	20	0.06	67	1330.12	550	18	0.08
15	999.74	450	20	0.06	68	1330.66	550	18	0.08
16	1507.18	450	20	0.08	69	1305.80	550	18	0.08
17	1510.84	450	20	0.08	70	1597.96	550	18	0.09
18	1465.95	450	20	0.08	71	1601.92	550	18	0.09
19	859.88	500	12	0.07	72	1627.88	550	18	0.09
20	836.04	500	12	0.07	73	922.50	550	20	0.06
21	866.24	500	12	0.07	74	916.84	550	20	0.06
22	1015.00	500	12	0.08	75	926.06	550	20	0.06
23	935.74	500	12	0.08	76	717.62	600	12	0.07
24	992.86	500	12	0.08	77	711.40	600	12	0.07
25	1081.32	500	15	0.07	78	695.97	600	12	0.07
26	1068.84	500	15	0.07	79	783.02	600	12	0.08
27	1086.70	500	15	0.07	80	809.46	600	12	0.08
28	1408.84	500	15	0.09	81	766.76	600	12	0.08
29	1399.44	500	15	0.09	82	899.94	600	12	0.09
30	1394.18	500	15	0.09	83	976.80	600	12	0.09
31	1239.40	500	18	0.07	84	904.50	600	12	0.09
32	1218.14	500	18	0.07	85	1077.66	600	15	0.08
33	1278.78	500	18	0.07	86	1082.62	600	15	0.08
34	1568.76	500	18	0.09	87	1086.42	600	15	0.08
35	1548.10	500	18	0.09	88	1426.34	600	18	0.09
36	1574.92	500	18	0.09	89	1424.70	600	18	0.09
37	636.64	550	10	0.06	90	1408.16	600	18	0.09
38	587.50	550	10	0.06	91	551.74	650	10	0.06
39	605.28	550	10	0.06	92	537.36	650	10	0.06
40	837.82	550	10	0.10	93	536.42	650	10	0.06
41	844.70	550	10	0.10	94	668.84	650	10	0.08
42	829.90	550	10	0.10	95	661.02	650	10	0.08
43	760.36	550	12	0.07	96	670.18	650	10	0.08
44	697.84	550	12	0.07	97	754.54	650	10	0.10
45	723.32	550	12	0.07	98	776.16	650	10	0.10
46	832.62	550	12	0.08	99	764.14	650	10	0.10
47	852.56	550	12	0.08	100	1063.22	650	15	0.08
48	846.18	550	12	0.08	101	1041.44	650	15	0.08
49	1040.40	550	12	0.09	102	1049.84	650	15	0.08
50	951.08	550	12	0.09	103	1366.60	650	20	0.08
51	964.34	550	12	0.09	104	1382.58	650	20	0.08
52	711.94	550	15	0.06	105	1388.52	650	20	0.08
53	749.16	550	15	0.06					

Table 2. ANOVA Table

Source	DF	Sum of Squares	Mean Square	F value	Pr>F
Model	4	8536718.8	3134179.7	606.17	0.0001
Error	100	352704.9	3520.8		
Corrected Total	104	8888793.7			

model could detect the tool conditions efficiently. It also tells us that the feed rate and depth of cut are particularly influential to the force in the regression model.

This research has assumed that all the cutting parameters were in control and were the same as those set in the CNC machine. However, in the actual manufacturing system, several conditions are difficult to control in the milling process, such as the depth of cut of material. Therefore, in the further research, using fuzzy logic or neural networks to solve the uncertain conditions could enhance the accuracy of the system.

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Table 3. Parameter Estimation Table

Parameter	Estimate	T for Ho: Parameter=0	Pr>|T|	Std Error of Estimate
Intercept	1767.12229	11.26	0.0001	156.891135
X_1	-1.12368	-11.53	0.0001	0.097479
X_2	-94.74684	-9.09	0.0001	10.425967
X_3	-14177.31222	-7.42	0.0001	1191.933906
X_1X_3	2103.51337	15.52	0.0001	135.550729

X1, X2, X3 represents the spindle speed, feed rate and depth of cut.

Table 4. Partial Testing Results using Training Data

Tool Condition	Fa (uN)	Fp (uN)	Speed (rpm)	Feed (ipm)	Depth (inch)	Error (%)	# of Tool	Success/ Failure
Good	851.20	882.78	450	15	0.06	3.67	1	S
Broken	1026.34	882.78	450	15	0.06	13.99	1	S
Good	1031.48	1040.11	450	20	0.06	0.84	2	S
Broken	1459.14	1040.11	450	20	0.06	28.72	2	S
Good	587.50	613.10	550	10	0.06	4.36	3	S
Broken	780.14	613.10	550	10	0.06	21.41	2	S
Good	1216.90	1117.93	550	15	0.08	8.13	4	S
Broken	1300.14	1117.93	550	15	0.08	14.01	4	S
Good	534.06	500.73	650	10	0.06	6.24	1	S
Broken	645.24	500.73	650	10	0.06	22.40	4	S
Good	776.16	775.04	650	10	0.10	0.14	3	S
Broken	994.12	775.04	650	10	0.10	22.04	1	S
Good	859.88	842.86	500	12	0.07	1.98	4	S
Broken	1077.74	842.86	500	12	0.07	21.79	4	S
Good	1081.32	1000.36	500	15	0.07	7.49	3	S
Broken	1091.54	1000.36	500	15	0.07	8.35	3	F
Good	783.02	841.14	600	12	0.08	7.42	2	S
Broken	1112.58	841.14	600	12	0.08	24.40	3	S
Good	1427.70	1519.21	600	18	0.09	6.63	2	S
Broken	1801.30	1519.21	600	18	0.09	15.66	3	S

Shaded areas are the results that make the wrong decision.

Table 5. Partial Testing Results using Testing Data

Tool Condition	Fa (uN)	Fp (uN)	Speed (rpm)	Feed (ipm)	Depth (inch)	Error (%)	# of Tool	Success/ Failure
Good	898.78	999.78	450	10	0.10	11.24	3	F
Broken	1304.64	999.78	450	10	0.10	23.19	2	S
Good	1363.50	1230.30	450	15	0.08	9.77	4	S
Broken	1819.16	1230.30	450	15	0.08	32.37	4	S
Good	740.04	750.26	550	10	0.08	1.38	2	S
Broken	905.50	750.26	550	10	0.08	17.14	2	S
Good	1453.58	1485.60	550	20	0.08	2.20	2	S
Broken	1678.28	1485.60	550	20	0.08	11.48	2	S
Good	674.36	658.05	650	15	0.06	2.42	1	S
Broken	872.72	658.05	650	15	0.06	24.60	4	S
Good	1276.62	1353.07	650	15	0.10	5.99	2	S
Broken	1455.96	1353.07	650	15	0.10	7.07	3	F
Good	1104.52	1064.16	500	12	0.09	3.65	2	S
Broken	1270.36	1064.16	500	12	0.09	16.23	2	S
Good	1368.76	1394.71	500	18	0.08	1.90	2	S
Broken	1719.94	1394.71	500	18	0.08	21.94	3	S
Good	1239.36	1235.50	600	15	0.09	0.31	1	S
Broken	1507.04	1235.50	600	15	0.09	18.02	2	S
Good	1024.46	1045.49	600	18	0.07	2.05	3	S
Broken	1278.56	1045.49	600	18	0.07	18.23	3	S

Shaded areas are the results that make the wrong decision.

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