Automatic recognition of tool wear on a face mill using a mechanistic modeling approach

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Abstract

A strategy is developed for identifying cutting tool wear on a face mill by automatically recognizing wear patterns in the cutting force signal. The strategy uses a mechanistic model development to predict forces on a lathe under conditions of wear and extends that model to account for the multiple inserts of a face mill. The extended wear model is then verified through experimentation over the life of the inserts. The predicted force signals are employed to train linear discriminant functions to identify the wear state of the process in a manner suitable for on-line application.

1. Introduction

The problem of monitoring tool condition in machining processes has become increasingly important in recent years. The high level of competition in the manufacturing industry has demanded that cutting tools be used and replaced in an efficient manner. Since the useful life of a cutting tool depends on many factors, such as the tool material, work material and cutting conditions, a predetermined replacement schedule invariably results in the under- or overuse of some tools. A strategy is therefore required which can identify the current tool condition and recognize when the tool has reached a level beyond usefulness. In addition, recent interest in unmanned or automatic process monitoring has led to the need to achieve process monitoring by automatic means. Automatically monitoring a process allows production personnel to be utilized in a more efficient manner and results in a more reliable and consistent monitoring activity, provided the automatic means are about as accurate or better than a human's performance.

Many strategies have been developed which attempt to use automatic means to identify tool condition in a manufacturing process. Direct measurement of tool wear [1] by means of optical methods, or through radioactive decay or electrical resistance monitoring, are generally more expensive and less flexible than techniques which infer tool condition from process signals. Such inferential, or indirect, methods include efforts to analytically relate characteristics of the cutting force [1-6], system vibration [7-9], acoustic emission [10-12], or power input [13] signals to the current state of the cutting tool. Emel and Kannatey-Asibu [12], for example, analyzed the frequency spectrum from the acoustic emission signal of a semi-orthogonal cutting process and were able to identify tool wear and breakage using a pattern classification system. Akgerman and Frisch [5] developed a control system to compensate for tool wear by

using the vertical cutting force from a turning process to estimate the worn-tool rake area.

Some important limitations are inherent in most of these previous studies. In particular, nearly all of the equations or algorithms suggested to relate a process signal to tool condition are specific to a certain set of cutting conditions (see ref. 13, for example). This necessitates the development and storage of a set of equation parameters or heuristics for each process condition of interest, including material or cut geometry changes. In addition, extensive wear tests must be carried out for the conditions or sets of conditions desired in order to obtain the various constants or parameters needed to predict the tool wear level (as in ref. 9). Clearly, a new approach capable of circumventing these costly drawbacks would benefit the effort to promote practical applications of the technology.

The study presented here represents an initial attempt to develop a methodology for monitoring process tool condition which can easily be applied to a process under virtually any cutting conditions and which does not require wear or life testing of the cutting tool. The use of a mechanistic model to describe the cutting force system is the key to the approach and the element which allows its advantages to be realized. The mechanistic model described here is for a multiple insert face milling process, the outputs of which include the force signals in the x , y and z directions (Fig. 1). The model, which is supported by experimental data taken over the life of a set of inserts, includes the effects of multiple insert run out and varying wear patterns on the milling inserts.

The identification strategy uses the mechanistic model to develop a pattern recognition system capable of monitoring tool condition on line. Simulated force signals are generated for increasing wear levels (in terms of the wear land width, VB) using the mechanistic model. Appropriate features are then extracted from these signals and employed in a pattern classification training procedure. The results of the training are discriminant functions which are used to identify the current state of the inserts in terms of wear based on features of the actual cutting signal.

The remainder of the paper describes the identification strategy in detail and includes a discussion of its practical utilization. Section 2 is a summary of the mechanistic model previously developed at the University of Illinois to predict single-insert wear forces [14-17] and multiple-insert force changes due to insert run out [18]. It also

Fig. 1. Coordinate frame relative to workpiece.

includes an extension of these models to the case of wear on multiple inserts. Section 3 explains the experimentation performed to verify the wear model and compares predicted and actual signals. The pattern recognition methodology is described in Section 4, including a listing of appropriate pattern features and results from applying the discriminant functions to the simulated data. Finally, Section 5 reveals the experimental results of classifying actual force signals from the face mill.

2. Mechanistic model for the face mill

A model capable of predicting the instantaneous cutting forces of a multiple insert milling process including the effects of insert run out and varying wear patterns on the inserts will be used to develop a computer simulation of the process. The simulation will, in turn, be used in place of traditional wear experiments to train a pattern classifier to recognize the wear state of a process.

2.1. The basic static force model

The basic face milling force model, developed at the University of Illinois in refs. 14-18 and derived from classical metal cutting research, is summarized by linear relationships between the cutting force, F_c , in a direction parallel to the cutting velocity, and the thrust force, F_t , in a direction perpendicular to the workpiece surface, and the chip area, A_c . The equations take the form

$$F_c = K_c A_c \quad (1)$$

$$F_t = K_t A_c \quad (2)$$

The chip area can be simply approximated by

$$A_c \approx f_i \sin(\theta_i) d \quad (3)$$

where f_i is the feed rate per tooth, d is the depth of cut, θ_i is the instantaneous angle that insert i makes with 0° (Fig. 1). The proportional constants, K_c and K_t , are actually functions of the average uncut chip thickness, $\bar{t}_c$ (which is approximately $f_i \sin(\theta_i)$), the cutting speed, V and the normal rake angle, α_n . The coefficients of the functions depend on the specific combination of tool and workpiece material used. The functions are described by

$$\ln(K_c) = a_0 + a_1 \ln(\bar{t}_c) + a_2 \ln(V) + a_3 \sin(\alpha_n) \quad (4)$$

$$\ln(K_t) = b_0 + b_1 \ln(\bar{t}_c) + b_2 \ln(V) + b_3 \sin(\alpha_n) \quad (5)$$

The coefficients, $a_0, \dots, a_3$ and $b_0, \dots, b_3$, are determined by fitting a least squares regression line to experimental values of K_c and K_t (found using eqns. (1) and (2)), obtained from running a series of tests in which $\bar{t}_c$, V and α_n are varied over a desired range of values. The models (sets of coefficients) for K_c and K_t are for a specific tool-workpiece combination and, once found, can be used for any future simulation using that combination.

Once K_c and K_t are determined, the force can be split into tangential, radial and longitudinal components according to

$$F_T = K_c A_c \quad (6)$$

$$F_R = K_t A_c \sin(\gamma_{Lc}) \quad (7)$$

$$F_L = K_t A_c \cos(\gamma_{Le}) \quad (8)$$

where γ_{Le} is the effective lead angle.

The effective lead angle, obtained by integrating over the chip length (defined below) as in refs. 14-16, is given by

$$\gamma_{Le} = \tan^{-1}[\tan(\gamma_L) + \Gamma_n/d(1 - \sin(\gamma_L))/\cos(\gamma_L)] \quad \text{for } d \geq r_n[1 - \sin(\gamma_L)] \quad (9)$$

$$\gamma_{Le} = \tan^{-1}[(2\Gamma_n/d - 1)^{0.5}] \quad \text{for } d < r_n[1 - \sin(\gamma_L)] \quad (10)$$

Here, γ_L is the nominal lead angle (side cutting edge angle), d is the depth of cut, and r_n is the tool nose radius.

2.2. Accounting for run out in the model

The effect on the forces due to radial insert run out can be included in the model by simply extending the chip area equation to include the radial runout ϵ on the current insert i and previous insert $i-1$:

$$A_c(i) = [f_i \sin(\theta_i) + \epsilon(i) - \epsilon(i-1)]d \quad (11)$$

The run out values can be obtained through measurements or estimated from the relative peak forces for each insert in the initial force signal as described in ref. 18.

2.3. Accounting for wear and multiple inserts in the model

The effect on the forces due to flank wear on the inserts is modeled by adding two force components, a force normal to the wear land, F_{NW} , and a force due to friction on the wear land, F_{FW} . The components [17, 19, 20] are proportional to the material hardness H (Brinell hardness number (BHN)), the wear land width (VB), the wear land length s , and the coefficient of sliding friction between the workpiece and tool materials μ . The relationships are given by

$$F_{NW} = HVBs \quad (12)$$

$$F_{FW} = \mu F_{NW} \quad (13)$$

The wear land is modeled with a constant width as shown in Fig. 2. The wear land length, s , is the length of contact between the tool flank and the fresh cut workpiece surface. It is assumed to be equal to the uncut chip length (see depth of cut in Fig. 2).

Fig. 2. Geometric flank wear model.

When cutting occurs on the tool nose radius and the side cutting edge (as in the current cutting tests), the chip length, l_c , is made up of two components, one along the nose radius, l_r , and one along the side cutting edge, l_s . The chip length is then given [14, 17] by

$$l_c = l_r + l_s \quad (14)$$

$$l_r = r_n(\phi_1 - \phi_0) \quad (15)$$

$$l_s = [d - r_n(1 - \sin(\gamma_L))]/\cos(\gamma_L) \quad (16)$$

where $\phi_1 = \pi/2 + \sin^{-1}(0.5f/r_n)$, $\phi_0 = \gamma_L$.

The modified force equations for the radial, longitudinal and tangential force components including the effects of wear (F_{RW} , F_{LW} , and F_{TW}) are found by adding appropriate components of the wear forces to the non-wear forces of eqns. (6)–(8), as in

$$F_{RW} = K_t A_{cw} \sin(\gamma_{Le}) + HVB \cdot s \sin(\gamma_{Lf}) \quad (17)$$

$$F_{LW} = K_t A_{cw} \cos(\gamma_{Le}) + HVB \cdot s \cos(\gamma_{Lf}) \quad (18)$$

$$F_{TW} = K_c A_{cw} + \mu HVB \cdot s \quad (19)$$

where γ_{Lf} is the effective lead angle for the force system on the tool flank. It is found by integrating ϕ , the angle made between F_{NW} and the radial direction, over the wear land length and then dividing by the wear land length, a method similar to the integration used to find the effective lead angle [15–17].

The chip area values in eqns. (17)–(19) have been modified to account for the change in chip geometry due to varying VB values for each insert. The size of each insert is reduced by a perpendicular distance δ_i due to friction from the workpiece. This distance, shown in Fig. 3, is obtained from

$$\delta_i = \cos(\alpha_e)VB(i) \sin(\theta_s)/\cos(\alpha_e + \theta_s) \quad (20)$$

where θ_s is the side relief angle of the insert, α_e is the effective rake angle described in ref. 17 as an integration over the chip length of the local effective lead angle, $\alpha_e(\phi)$, divided by the chip length, l_c . The local effective lead angle follows the eqn.

$$\alpha_e(\phi) = \sin^{-1}[\sin^2(i(\phi)) + \cos^2(i(\phi)) \sin(\alpha_n(\phi))] \quad (21)$$

Fig. 3. Insert with volume removed by wear.

Fig. 4. Decrease in chip thickness due to wear.

where $i(\phi)$ and $\alpha_n(\phi)$ are the inclination and normal rake angles [21], and ϕ is the angle a normal to the cutting edge makes with the radial direction, measured in a plane normal to the cutting velocity.

The decrease in chip thickness for insert i is shown in Fig. 4 as

$$\Delta t_c(i) = \delta_i / \cos(\gamma_i) \quad (22)$$

The chip area calculation including wear effects then becomes

$$A_{cw}(i) = [f_i \sin(\theta_i) + \epsilon(i) - \epsilon(i-1) - \Delta t_c(i) + \Delta t_c(i-1)]d \quad (23)$$

3. Experimental details

An experiment was performed to verify the mechanistic wear model described above. The wear land width was measured on a pair of slightly worn coated carbide inserts and the inserts were mounted in a face milling cutter (10.16 cm diameter). The cutter was driven by a motorized spindle on a two-slide test bed provided by the Ingersoll Milling Machine Company on which a workpiece/fixture assembly is mounted. The 76.2×152.4 mm workpiece, composed of gray cast iron (BHN = 229 kg mm⁻²), was attached to a force dynamometer which sensed the x , y and z direction forces. The instantaneous forces were then recorded by a personal computer by way of a data acquisition system. The experimental environment is summarized in Fig. 5. After three hours of cutting and recording force measurements, the inserts were removed and the wear land was measured again. The remaining process conditions are summarized in Table 1.

The appropriate K_c , K_t models for the tool-workpiece combination used were determined empirically from a series of eight fly cutting tests performed for the current experiment (using the method in ref. 15). The models were calculated to be

$$\ln(K_c) = 10.2275 - 0.46594 \ln(\bar{t}_c) - 0.08805 \ln(V) \quad (24)$$

$$\ln(K_t) = 8.42213 - 0.80352 \ln(\bar{t}_c) - 0.02059 \ln(V) \quad (25)$$

The rake angle was not varied during the experimentation, and therefore no α_n term was included.

(a)

(b)

Fig. 5. (a) Workpiece and dynamometer (mounted on slide) and spindle; (b) Macintosh II based data acquisition system.

TABLE 1

Process conditions for cutting experiment

Cutting velocity	1200 rev min ⁻¹
Feed per tooth	0.1694 mm per tooth
Depth of cut	1.016 mm
Lead angle	15°
Radial rake angle	-7°
Axial rake angle	-7°
Tool nose radius	1.1906 mm
Flank relief angle	11°
Radial run out	
Insert 1	0 mm (ref.)
Insert 2	0.0381 mm
Initial wear (VB)	
Insert 1	0.1016 mm
Insert 2	0.1270 mm
Final wear (VB)	
Insert 1	0.1905 mm
Insert 2	0.3810 mm

The initial force signals, and the force signals obtained after approximately three hours of machining, are shown in Figs. 6, 7 and 8 for a full rotation of the cutter. The corresponding signals generated using the mechanistic model simulation are shown below each of the observed force signals. In all the graphs the boxed line represents the force signal from the beginning of the experiment. The experimental signals are passed through a FIR low-pass digital filter [22] (blocking all frequencies above 450 Hz). The solid line is the signal at the end of the experiment after significant wear had occurred. Since only two inserts were used for the test, cutting only took place about half of the time, resulting in a zero level force for that portion of the rotation. In each case, the insert with greater radial run out shows a greater magnitude of force (the negative x -force is due to the defined x direction in Fig. 1). The plots show that the forces for the insert with more run out rose approximately 70%–80% over the course of the tests. The other insert's forces rose nearly 500%.

A comparison of the observed signals with those generated by the model simulation reveals that the predicted forces are reasonably close to the experimental values. For the beginning of the experiment (initial wear), the model predicts forces within about $\pm 5\%$ of the observed signals. The worn condition (final wear) predictions are also fairly good, although the x -force is overpredicted by about 15% and 40% for the two insert profiles. This is most probably due to the difficulty experienced in measuring an accurate wear land width on the severely worn inserts.

The force signals were also compared in the frequency domain, under the assumption that the cyclical data would be well represented by a plot of the power spectrum. Figure 9 gives spectral plots of the observed and predicted x -direction force signals for both the initial and final wear conditions. (The plots only include frequencies below 200 Hz because the mechanistic model only accounts for the static, low frequency portion of the force signal, i.e. no vibrational or dynamic components were included.) The two most important peaks in the spectra occur at 20 Hz (the spindle frequency) and 40 Hz (the tooth-passing frequency). In both the observed and predicted cases, the peak at 20 Hz decreases slightly as significant wear appears, while the 40 Hz peak

Fig. 6. (a) Observed x -force signals, initial and final wear; (b) simulated x -force signals, initial and final wear.

increases by a larger amount. Since the model seems to predict well in the frequency domain, the magnitudes of these peaks were selected as possible features to be used in the pattern recognition system described in the next section.

4. Pattern recognition methodology

The automatic detection of wear on the inserts of a face mill requires some pattern recognition strategy which can signal wear when it occurs. Instead of using extensive wear tests to train a pattern classifier, the simulation model developed in Section 2 can be used to generate training signals. Appropriate features are then extracted from these simulated force signals and formed into feature vectors, or patterns.

Fig. 7. (a) Observed y -force signals, initial and final wear; (b) simulated y -force signals, initial and final wear.

These vectors are used to obtain the coefficients of (*i.e.* to train) a linear discriminant function which acts as a minimum-distance classifier [23] for any future vectors presented for classification. A minimum-distance classifier is actually a plane in hyperspace (with dimension equal to the number of features minus one) which separates the subspaces (one for each category) that make up the space spanned by the feature vectors. Three categories are used in the present study, although more are certainly possible.

The simulation model was used to generate force signals to train the pattern classifier. For this study it was desired that only one signal (x , y or z direction) be used for classification. The x -force was chosen since it represents components of both the radial and tangential forces (y -force could also have been chosen) and would therefore contain more information than the z -force, which is essentially the longitudinal force. Three sets of five simulated force signals each were generated using the mechanistic

Fig. 8. (a) Observed z-force signals, initial and final wear; (b) simulated z-force signals, initial and final wear.

model. Each set corresponds to one of three categories — either initial wear, intermediate wear, or final wear. The only difference between the simulated signals was the insert wear levels assumed for each run. The wear levels for all of the training signals are shown in Table 2, according to their predetermined category.

After considering many alternative features that might represent the signals, 11 features from both the time and frequency domain were chosen and collected for each signal. The features selected are:

- 1 RMS: the root mean square, or standard deviation, of the signal (N)
- 2 AVGS: the average slope of the time domain signal ($N s^{-1}$)

Fig. 9. (a) Spectrum of observed x -force, initial and final wear; (b) spectrum of simulated x -force, initial and final wear.

3 VARS: the variance of the slope ($\times 10^8 \text{ (N s}^{-1}\text{)}^2$)

4 ALLOW: the area under the spectrum in the low frequency range (between half the spindle frequency and twice the tooth-passing frequency) (N^2)

5 PROT: the spectral power at the spindle rotation frequency ($\text{N}^2 \text{ Hz}^{-1}$)

6 PTOOT: the spectral power at the tooth-passing frequency ($\text{N}^2 \text{ Hz}^{-1}$)

7 PR/PT: the ratio of PROT to PTOOT

8 PR/PT-S: PR/PT scaled by the signal standard deviation (RMS)

9 PT-PR: the difference PTOOT-PROT ($\text{N}^2 \text{ Hz}^{-1}$)

Tables 3-5 show the actual values of each feature for the simulated signals.

Since the listed features were chosen somewhat haphazardly, a procedure was followed for determining the features with optimal discriminating power. The procedure

TABLE 2

Insert wear patterns (VB in mm) for simulations

Initial wear		Intermediate wear		Severe wear	
Insert 1	2	Insert 1	2	Insert 1	2
0.1016	0.1270	0.1346	0.2591	0.1880	0.3099
0.0965	0.1245	0.1245	0.2311	0.1930	0.3327
0.1067	0.1346	0.1270	0.2794	0.1676	0.3023
0.1016	0.1321	0.1194	0.2184	0.1727	0.3048
0.0991	0.1194	0.1270	0.2464	0.1854	0.3073

TABLE 3

Simulated feature sets, z_{1j} , initial wear condition

	Set					m_1 (avg)
	1	2	3	4	5	
RMS	186.824	182.688	191.673	187.892	183.310	186.477
AVGS	9.759	11.939	16.067	-0.845	-5.249	6.334
VARS	0.1201	0.1132	0.1349	0.1264	0.1084	0.1206
ALOW	30392.0	29117.8	31982.9	30754.1	29303.8	30310.1
PROT	822.94	806.06	807.92	800.51	842.11	815.91
PTOOT	1257.10	1181.32	1394.34	1313.31	1151.78	1259.57
PR/PT	0.6546	0.6823	0.5794	0.6095	0.7311	0.6478
PR/PT_S	0.0035	0.0037	0.0030	0.0032	0.0040	0.0035
PT-PR	434.16	375.26	586.42	512.80	309.67	443.66

TABLE 4

Simulated feature sets, z_{2j} , intermediate wear condition

	Set				
	1	2	3	4	5
RMS	257.684	238.779	222.677	230.150	247.142
AVGS	-20.866	-10.645	-9.621	-3.487	-7.860
VARS	0.3597	0.2926	0.3833	0.2638	0.3229
ALOW	57226.5	49254.5	59420.8	45817.6	52711.2
PROT	619.97	649.19	571.96	662.78	627.15
PTOOT	3559.33	2919.90	3787.64	2644.65	3208.99
PR/PT	0.1742	0.2223	0.1510	0.2506	0.1954
PR/PT_S	0.0007	0.0009	0.0007	0.0011	0.0008
PT-PR	2939.37	2270.72	3215.68	1981.87	2581.85

TABLE 5

Simulated feature sets, z_{3j} , final wear condition

	Set				
	1	2	3	4	5
RMS	314.933	329.523	298.652	303.056	312.130
AVGS	6.717	-15.355	17.699	-9.070	184.307
VARS	0.5801	0.6480	0.5156	0.5329	0.5683
ALLOW	85141.2	93123.1	76637.0	78878.8	83635.5
PROT	638.81	611.46	611.46	617.12	638.81
PTOOT	5641.16	6271.46	5027.69	5192.41	5525.46
PR/PT	0.1132	0.0975	0.1216	0.1189	0.1156
PR/PT S	0.0004	0.0003	0.0004	0.0004	0.0004
PT-PR	5002.36	5660.00	4416.23	4575.29	4886.66

[12] involves the calculation for each feature of a criterion J , which is a measure of the ratio of the between-category scatter of patterns to the overall scatter of patterns. The pattern vectors are denoted by z_{ij} ($i=1$ to 3 for the number of categories, $j=1$ to 5 for the number of patterns in each category, denoted n_i). A procedure for calculating J is outlined as follows.

(i) An average feature vector m_i was calculated using

$$m_i = \frac{1}{n_i} \sum_{j=1}^{n_i} z_{ij} \quad (26)$$

for each category ($i=1$: initial, $i=2$: intermediate, and $i=3$: final wear) from Tables 3, 4 and 5. Note that n_i equals 5 for each category. As an example, m_1 is shown in the last column of Table 3.

(ii) The deviation of the j th pattern set z_{ij} of category i from the category mean $(z_{ij} - m_i)$ was found for all 15 pattern vectors.

(iii) The within-category scatter matrices were obtained using

$$S_i = \frac{1}{n_i} \sum_{j=1}^{n_i} (z_{ij} - m_i)(z_{ij} - m_i)^T \quad (27)$$

where $i=1$ to 3, $n_i=5$, and T denotes the matrix transpose.

(iv) The overall scatter matrix uses *a priori* probabilities, ρ_i equal to n_i divided by the total number of pattern sets, and was found by

$$S_w = \sum_{i=1}^3 \rho_i S_i \quad (28)$$

where $\rho_1 = \rho_2 = \rho_3 = 0.33$, and k equals the number of categories, 3.

(v) An overall mean was found:

$$m = 0.33(m_1 + m_2 + m_3) \quad (29)$$

(vi) The between-category scatter matrix was calculated according to

$$S_b = \sum_{i=1}^k \rho_i (m_i - m)(m_i - m)^T \quad (30)$$

(vii) For the r th feature, J was calculated by the ratio

$$J = S_b(r, r) / S_w(r, r) \quad (31)$$

The results of the optimal feature selection are given in Table 6 with the J value for each feature and the five best features indicated (it was decided to utilize only one of PR/PT_S, PR/PT, and PT-PR due to their similarity).

To train the minimum-distance classifier a single feature vector was used to represent each category. These representative vectors (Table 7), P_1 , P_2 and P_3 , which are subsets on the m_i (scaled to be roughly between 0 and 1) calculated in eqn. (26), were found by averaging in each category over the five selected features. Both the representative vectors and the actual signal feature vectors to be classified were scaled to be between 0 and 1. For example, each RMS feature is multiplied by 10^{-3} (see Tables 3, 7). According to Nilsson [23], a linear discriminant function for each category can then be determined by

$$g_i(z) = z_1 P_{i1} + z_2 P_{i2} + \dots + z_d P_{id} - \frac{1}{2} P_i \cdot P_i \quad (32)$$

where $z_1, z_2, \dots, z_d$ represent the d features from a signal to be classified. Here, $d=5$, the number of features used for classification.

The three calculated discriminant functions are:

$$g_1(z) = 0.1865z_1 + 0.1206z_2 + 0.3031z_3 + 0.1260z_4 + 0.3499z_5 - 0.2795 \quad (33)$$

TABLE 6

Features in preferential order of criterion J

	J
PR/PT_S ^a	39.703
PR/PT	39.588
VARs ^a	36.778
RMS ^a	28.484
PT-PR	25.429
PTOOT ^a	25.045
ALLOW ^a	24.230
PROT	17.945
AVGS	0.203

^aDenotes feature selected for discrimination.

TABLE 7

Averaged (scaled) feature vectors used with minimum-distance classifier

	Initial, P_1	Intermediate, P_2	Final, P_3
RMS	0.18648	0.23929	0.31166
VARs	0.12062	0.32446	0.56898
ALLOW	0.30310	0.52886	0.83483
PTOOT	0.12596	0.32241	0.55316
PR/PT_S	0.34989	0.08330	0.03650

$$g_2(z) = 0.2393z_1 + 0.3245z_2 + 0.5289z_3 + 0.3224z_4 + 0.0833z_5 - 0.5531 \quad (34)$$

$$g_3(z) = 0.3117z_1 + 0.5690z_2 + 0.8348z_3 + 0.5532z_4 + 0.0365z_5 - 1.4251 \quad (35)$$

To classify a signal, the appropriate features are extracted from the signal (a FORTRAN program was utilized to automatically determine the features from the force signal). The three discriminant functions are then evaluated using the extracted feature values (z_1 : RMS, z_2 : VARS, z_3 : ALOW, z_4 : PTOOT, z_5 : PR/PT_S), and the signal is assigned to the category (1, 2 or 3) corresponding to the function with the greatest value (g_1 , g_2 or g_3).

The classification strategy was tested on a set of simulated force profiles. Twelve signals were generated using the wear levels listed in Table 8. The signals are meant to represent a probable progression of wear from the initial to the final stage. The calculated values for the features $z_1, z_2, \dots, z_5$ are shown in Table 8 next to the wear levels. The last column reveals the category into which the signal was placed by the discriminant functions. The first four signals fell into category 1, initial wear. The middle four were placed in the intermediate category, and the four signals with the most wear were placed in category 3.

To test the robustness of the classification scheme on the simulated data, the 12 tests were then rerun under varying conditions of spindle speed, radial insert run out, workpiece material hardness, and tool-workpiece coefficient of friction. The results can be seen in Table 9. The first column repeats the original classifications from Table 8. The next three columns show the classification results from varying spindle speed (up to 25%) from the original 1200 rev min⁻¹ to speeds of 900, 1100 and 1300 rev min⁻¹. Varying the speed did have a significant effect on classification, especially when the speed was reduced to 900 rev min⁻¹. The remainder of the table gives the results from deviations in the run out (up to 20%) from the original 0.0381 mm, the hardness (24%) from its original value of 229 BHN, and the coefficient of friction (33%), which was first assumed to be 0.3. The greatest effect was seen when the hardness varied.

TABLE 8

Classification results for simulated data

Wear (V/B) on insert	Feature set						
	RMS	VARS	ALOW	PTOOT	PR/PT_S	Response	
	z_1	z_2	z_3	z_4	z_5		
0.0000	0.1245	0.1827	0.1132	0.2912	0.1181	0.3752	1
0.1016	0.1270	0.1868	0.1201	0.3039	0.1257	0.3514	1
0.1067	0.1340	0.1917	0.1349	0.3198	0.1394	0.3006	1
0.1143	0.1379	0.2108	0.1971	0.3856	0.2002	0.1733	1
0.1245	0.2011	0.2388	0.2926	0.4925	0.2920	0.0926	2
0.1321	0.2540	0.2538	0.3457	0.5553	0.3431	0.0710	2
0.1422	0.2710	0.2683	0.3985	0.6199	0.3930	0.0589	2
0.1499	0.2845	0.2791	0.4393	0.6700	0.4309	0.0499	2
0.1575	0.3302	0.3066	0.5556	0.8066	0.5400	0.0332	3
0.1676	0.3023	0.2987	0.5156	0.7664	0.5028	0.0403	3
0.1854	0.3073	0.3121	0.5683	0.8364	0.5526	0.0372	3
0.1930	0.3327	0.3295	0.6480	0.9312	0.6272	0.0291	3

TABLE 9

Response sensitivity analysis (simulated data)

Test	Orig. resp.	Speed (rev. min ⁻¹)			Run out ($\times 0.01$ mm)			Hardness (BHN)			μ	
		900	1100	1300	3.05	3.91	4.19	175	220	250	0.2	0.4
1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1
4	1	2	2	1	1	1	1	1	1	2	1	1
5	2	2	2	2	2	2	2	1	2	2	2	2
6	2	2	2	2	2	2	2	1	2	2	2	2
7	2	3	2	2	2	2	3	2	2	3	2	2
8	2	3	3	2	3	2	3	2	2	3	2	3
9	3	3	3	3	3	3	3	2	3	3	3	3
10	3	3	3	3	3	3	3	2	3	3	3	3
11	3	3	3	3	3	3	3	2	3	3	3	3
12	3	3	3	3	3	3	3	2	3	3	3	3

In fact, when the hardness was set equal to 175 BHN, no signals were placed in category 3.

These results suggest that added consideration should be used with the values for speed and hardness in the simulator. For example, a machine setting of 1300 rev min⁻¹ may result in an actual spindle rotation speed which varies between 1260 and 1280 rev min⁻¹. The classifier is especially sensitive to this deviation between the desired and actual speeds. A simulator speed of 1270 rev min⁻¹ (instead of the originally considered 1300 rev min⁻¹) may lead to the best results for this example.

5. Classification results and discussion for experimental data

The discriminant functions obtained in the previous section were applied to the experimental data collected during the wear tests. A total of 26 force signals were collected, starting with the first test after 1 min of cutting and continuing over nearly 175 min. The measured *VB* values on the inserts prior to machining were 0.1016 and 0.1270 mm. After machining the wear land widths had increased to 0.1905 and 0.3810 mm. Table 10 provides the results of classification for each signal according to how many minutes of cutting had taken place when it was collected. Associated with each signal are the values of the three discriminant functions (eqns. (33)–(35)) and the category into which it was placed.

The results were very good for the classification system. Of the signals taken in the first 35 min of cutting 6 out of 6 were correctly classified as belonging to category 1 (initial wear). Of the 12 signals collected between 35 and 115 minutes, 11 were correctly placed in category 2 (intermediate wear), with the incorrect signal placed in category 3. Similarly, 7 out of the 8 signals tested from the final 60 min of cutting were correctly identified as category 3 (final wear) signals, with one being put into category 2.

The wear detection strategy can easily be extended to wear detection during cutting under different conditions. The mechanistic model described in Section 2 can

TABLE 10

Classification results for experimental data

Time (min)	$g_1(x)$	$g_2(x)$	$g_3(z)$	Category
1	0.12067	0.11841	-0.09628	1
4	0.14308	0.08162	-0.16959	1
7	0.15283	0.07281	-0.18799	1
16	0.13227	0.04938	-0.22089	1
25	0.13070	0.05221	-0.22142	1
34	0.16033	0.12529	-0.10022	1
40	0.21544	0.24316	0.09625	2
49	0.15879	0.16918	-0.01631	2
55	0.18179	0.23244	0.08802	2
60	0.16799	0.21524	0.06113	2
67	0.16325	0.19039	0.01829	2
75	0.16712	0.21855	0.06756	2
79	0.26616	0.46541	0.47946	3
85	0.25216	0.40939	0.38401	2
88	0.23545	0.36979	0.31819	2
97	0.23227	0.36954	0.31980	2
103	0.21583	0.33040	0.25208	2
112	0.19703	0.29619	0.19635	2
118	0.31846	0.57113	0.65384	3
127	0.31088	0.55465	0.62583	3
133	0.30886	0.54150	0.60092	3
139	0.24043	0.40432	0.37627	2
149	0.29289	0.50305	0.53610	3
157	0.42239	0.79627	1.02537	3
166	0.31934	0.60215	0.71170	3
172	0.29032	0.54294	0.61362	3

be used to model face milling processes over a wide range of cutting conditions, tool and workpiece geometries, insert configurations, and cutting materials. Initial cutting tests may be required to determine the run out pattern or to obtain a model for the constants K_t and K_c . The simulation of wear on the inserts is at the discretion of the user, who determines the categories and levels of VB to be recognized.

The detection strategy proposed is suitable for on-line application using automatic means. The use of the simulator to create training patterns, the optimal feature selection, and the training of the discriminant functions are all performed off-line prior to machining. Once obtained, however, the functions are applicable for the life of the inserts. For on-line application, the force signal must be processed to determine the values of the appropriate features (such as power spectrum values, signal variance, etc.). The features are then entered into the functions and the signal is classified. Current technology and computational efficiency have made the calculation of power spectrum and other signal properties sufficiently fast for on-line classification of the process state.

6. Conclusion

The basic structure of an automatic pattern recognition system which identifies the approximate wear level on the inserts of a face mill has been developed. The

system is designed to classify an actual process as to its wear state based on the x -direction force signal generated on line. The parameters of the discriminant function used for classification, however, are derived almost entirely from simulated signals obtained by way of a static mechanistic force model of the milling process. Although other methods of training discriminant functions exist, the minimum-distance method described here performed well in classifying the observed signals according to the level of wear experienced. The strategy was also tested under varying process conditions and was able to show adequate robustness in terms of its performance in the face of various modeling errors. The advantages of this classification strategy are its ability to be readily applied to virtually any set of process conditions and the elimination of the need for extensive wear tests to train the pattern classifiers. The system is limited mainly by the sophistication of the mechanistic model and the amount of prior knowledge of expected wear levels.

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